Feature Optimization for Predicting Readability of Arabic L1 and L2

Hind Saddiki,†‡ Nizar Habash,† Violetta Cavalli-Sforza,* and Muhamed Al Khalil†
†New York University Abu Dhabi
‡Mohammed V University in Rabat
⋆Al Akhawayn University in Ifrane
{hind.saddiki,nizar.habash,muhamed.alkhalil}@nyu.edu, v.cavallisforza@aui.ma

Abstract

Advances in automatic readability assessment can impact the way people consume information in a number of domains. Arabic, being a low-resource and morphologically complex language, presents numerous challenges to the task of automatic readability assessment. In this paper, we present the largest and most in-depth computational readability study for Arabic to date. We study a large set of features with varying depths, from shallow words to syntactic trees, for both L1 and L2 readability tasks. Our best L1 readability accuracy result is 94.8% (75% error reduction from a commonly used baseline). The comparable results for L2 are 72.4% (45% error reduction). We also demonstrate the added value of leveraging L1 features for L2 readability prediction.

1 Introduction

The purpose of studies in readability is to develop and evaluate measures of how well a reader can understand a given text. Computational readability measures, historically shallow and formulaic, are now leveraging machine learning (ML) models and natural language processing (NLP) features for automated, in-depth readability assessment systems. Advances in readability assessment can impact the way people consume information in a number of domains. Prime among them is education, where matching reading material to a learner’s level can serve instructors, book publishers, and learners themselves looking for suitable reading material. Content for the general public, such as media and news articles, administrative, legal or healthcare documents, governmental websites and so on, needs to be written at a level accessible to different educational backgrounds. Efforts in building computational readability models and integrating them in various applications continue to grow, especially for more resource-rich languages (Dell’Orletta et al., 2014a; Collins-Thompson, 2014).

In this paper, we present a large-scale and in-depth computational readability study for Arabic. Arabic, being a relatively low-resource and morphologically complex language, presents numerous challenges to the task of automatic readability assessment. Compared to work done for English and other European languages, efforts for Arabic have only picked up in recent years, as better NLP tools and resources became available (Habash, 2010). We evaluate data from both Arabic as a First Language (L1) and Arabic as a Second or Foreign Language (L2) within the same experimental setting, to classify text documents into one of four levels of readability in increasing order of difficulty (level 1: easiest; level 4: most difficult). This is a departure from all previously published results on Arabic readability, which have only focused on either L1 or L2. We examine a larger array of predictive features combining language modeling (LM) and shallow extraction techniques for lexical, morphological and syntactic features. Our best L1 Readability accuracy result is 94.8%, a 75% error reduction from a baseline feature set of raw and shallow text attributes commonly used in traditional readability formulas and simpler computational models (Collins-Thompson, 2014). The comparable results for L2 are 72.4%, a 45% error reduction from the corresponding baseline performance in L2. We leverage our rich Arabic L1 resources to support Arabic L2 readability. We increase the L2 accuracy to 74.1%, an additional 6% error reduction, by augmenting the L2 feature set with features based on L1-generated language models (LM).
### Comparative Summary of Recent Work and Our Current Study

| Corpus                  | Size (tokens) | L1 Features | L2 Features | LM Features | Results Reported          |
|-------------------------|---------------|-------------|-------------|-------------|---------------------------|
| Al-Khalifa and Al-Ajlan (2010) | 150 docs (57,089) | ✓            | ✓           | ✓           | Accuracy: 77.8%          |
| Al Tamimi et al. (2014)   | 1,196 docs (432,230) | ✓            | ✓           | ✓           | Accuracy: 83.2%          |
| Cavalli-Sforza et al. (2014) | 114 docs (49,666) | ✓            | ✓           | ✓           | Accuracy: 91.3%          |
| Forsyth (2014)            | 179 docs (74,776) | ✓            | ✓           | ✓           | F-Score: 71.9%           |
| Saddiki et al. (2015)     | 251 docs (88,023) | ✓            | ✓           | ✓           | F-Score: 73.4%           |
| El-Haj and Rayson (2016)  | 73,000 lines (1,8M) | ✓            | ✓           | ✓           | Spearman R: .329         |
| Nassiri et al. (2017)     | 230 docs (60,000) | ✓            | ✓           | ✓           | F-Score: 90.5%           |
| **Our Work**             | L1: 27,688 docs (6.9M) | ✓            | ✓           | ✓           | L1 Accuracy: 94.8%       |
|                         | L2: 576 docs (186,125) | ✓            | ✓           | ✓           | L2 Accuracy: 72.4%       |

Table 1: Comparative summary of recent work and our current study on computational readability for Arabic in terms of corpus size, focus on L1 or L2, use of shallow vs. deep features requiring heavier processing for extraction from the text, use of language models in generating features. Results reported are presented for reference rather than direct comparison.

## 2 Background and Related Work

Computational readability assessment presents a growing body of work leveraging NLP to extract complex textual features, and ML to build readability models from corpora, rather than relying on human expertise or intuition (Collins-Thompson, 2014). Approaches vary depending on the purpose of the readability prediction model, e.g., measuring readability for text simplification (Aluisio et al., 2010; Dell’Orletta et al., 2014a; Al Khalil et al., 2017), selecting more cognitively-predictive features for readers with disabilities (Feng et al., 2009) or for self-directed language learning (Beinborn et al., 2012). Features used in predicting readability range from surface features extracted from raw text (e.g. average word count per line), to more complex ones requiring heavier text processing such as syntactic parsing features (Heilman et al., 2007, 2008; Beinborn et al., 2012; Hancke et al., 2012). The use of language models is increasingly favored in the literature over simple frequency counts, ratios and averages commonly used to quantify features in traditional readability formulas (Collins-Thompson and Callan, 2005; Beinborn et al., 2012; François and Miltsakaki, 2012). We evaluate features extracted using both methods in this study.

There is a modest body of work on readability prediction for Arabic with marked differences in modeling approaches pursued, feature complexity, dataset size and type (L1 vs. L2), and choice of evaluation metrics. We build our feature set with predictors frequently used for Arabic readability studies in the literature, and augment it with features from work carried out on other languages.

We do organize our feature set on two dimensions: (a) the way features are quantified: basic statistics for frequencies and averages, or language modeling perplexity scores; (b) the depth of processing required to obtain said features: directly from raw text, morphological analysis, or syntactic parsing.

In Table 1, using these two dimensions, we situate ours and previous work and establish a common baseline of raw base features (i.e. traditional measures (DuBay, 2004)) to compare to.

### Use of Language Modeling

Features such as frequency counts, averages and other ratios seem to dominate the literature for Arabic readability. These are usually referred to as traditional, shallow, basic or base features in the literature for their simplicity. In contrast, Al-Khalifa and Al-Ajlan (2010) add word bi-gram perplexity scores to their feature set, a popular readability predictor in English and other languages.

### Depth of Features

The set of features used in previous readability studies exhibit a range of complexity in terms of depth of processing needed to obtain them. While some studies have relied on raw text features requiring shallow computations (Al-Khalifa and Al-Ajlan, 2010; Al Tamimi et al., 2014; El-Haj and Rayson, 2016), most augment their feature set with lexical and morphological information by processing the text further and extracting features such as lemmas, morphemes, and part-of-speech tags (Cavalli-Sforza et al., 2014; Forsyth, 2014; Saddiki et al., 2015; Nassiri et al., 2017). We add another level of feature complexity by extracting features from syntactic parsing, used in readability assessment for other languages but so far untried for Arabic (Table 1).
3 Features for Readability Prediction

Textual features associated with degree of readability range from surface attributes such as text length or average word length, to more complex ones quantifying cohesion or higher-level text pragmatics. Naturally, the shallower attributes are also the easiest and least costly to extract from a text, as opposed to the deeper and more computationally challenging features.

Notation We define the notation used in the remainder of this paper to describe features, ranges of features and classification feature sets:

- An individual feature is expressed as $F[i]$, $i \in [1, 146]$ is a number assigned to the feature as defined in Table 2; e.g., $F[1]$ for number of characters per document
- A feature range is expressed as $F[i-j]$, $1 \leq i \leq j \leq 146$ and indicates a group of features similar in nature with numbers assigned to them as defined in Table 2
- A classification feature set or subset is expressed as $FEAT_{Super}^{Subscript}$. The superscript indicates whether the set contains features that are {Raw, Morph, Syn or all three Raw.Morph.Syn}. The subscript indicates whether the features are computed as {Base, LM, or both Base.LM} quantities.

The feature list we have compiled (Table 2) is inspired by previous work for Arabic and other languages, and is organized by category as discussed in the previous section.

Base features $FEAT_{Base}$ range from shallow estimates, like word count or average sentence length, to others requiring more advanced processing, e.g. average parse tree depth for sentences in a document. LM-based features $FEAT_{LM}$ are a range of 12 perplexity scores obtained on n-gram models (uni-, bi- and tri-grams) built per level of readability. For instance, the first 3 features in the range $F[51-62]$ are the following: $F[51]$ Level 1 character unigrams, $F[52]$ Level 1 character bigrams, $F[53]$ Level 1 character trigrams.

We also distinguish three category labels for the depth of NLP-based processing required to extract the different features:

- $FEAT_{Raw}$: raw text extraction with minimal processing: Several formulas making use of raw text features have been successfully adopted and adapted in English and other languages, their appeal largely due to them being easy to understand and compute.
- $FEAT_{Morph}$: morphological analysis providing lexical and morpho-syntactic information: Readability is heavily influenced by vocabulary and word-level information (DuBay, 2007). Having word-level lexical and morpho-syntactic information can better inform the predictions.
- $FEAT_{Syn}$: syntactic parsing providing parse tree information and dependencies: Syntactic features have shown promise in improving readability prediction, especially for L2 reading. (Hancke et al., 2012) (Heilman et al.,

| 8 FEAT Raw Base * | 20 FEAT Morph Base |
|-------------------|---------------------|
| F[1] Characters   | F[9] Morphemes      |
| F[2] Tokens      | F[10] Verb Forms    |
| F[3] Characters/Tokens | F[11] Pronouns     |
| F[4] Sentences   | F[12] Psv. Verbs   |
|                   | F[13] Open-class Tokens |
|                   | F[14] Closed-class Tokens |
|                   | F[15] Nouns         |
|                   | F[16] Verbs         |
|                   | F[17] Pronouns      |
|                   | F[18] Nouns         |
| 24 FEAT Raw LM   | 48 FEAT Morph LM    |
| F[29-36] CATiB dependency | F[63-74] LM perplexity of morphemes |
| F[37] Average parse tree breadth | F[75-86] LM perplexity of lemmas |
| F[38] Average parse tree depth | F[87-98] LM perplexity of POS |
| F[51-62] LM perplexity of Words * | F[99-110] LM perplexity of lemma-POS mix |
| 36 FEAT Syn LM   |                     |
| F[111-122] LM perplexity of CATiB POS | F[135-146] LM perplexity of CATiB dependency |

Table 2: Our feature set organized by category. All features are calculated per document, and sentence level features are averaged per document. Feature sets or features marked by an * are inspired by previous work on Arabic readability.
‘History offers us plenty of lessons and sermons.’; BOTTOM: Table of FeatRawBase feature values computed for the example sentence given.

Figure 1: TOP: Example of linguistic annotations for the sentence ‘History offers us plenty of lessons and sermons.’; BOTTOM: Table of FeatRawBase feature values computed for the example sentence given.

In Table 2, most base features are computed simply by counting occurrences within the document. Ratios are expressed as mathematical fractions, such as F[3], F[5], F[11] and so on. LM perplexity is computed per readability level (1, 2, 3, and 4) on (uni-, bi- and tri-)grams language models, generating 4 level scores per n-gram and a total of 12 perplexity scores per feature. Figure 1 gives an idea of the linguistic annotation extracted for an example sentence and illustrates how feature values are computed for the FeatRawBase subset. The annotation was generated using the CamelParser. POS tagsets used are POS6 (Habash and Roth, 2009) and a higher granularity POS34 (Habash et al., 2012). We refer the user to Shahrour et al. (2016) for further details.

We elaborate next on the feature names in Table 2:

- F[6] Al-Heeti readability formula for Arabic as presented by Al-Khalifa and Al-Ajlan (2010) and other subsequent work.
- F[7], F[8] represent the Automated Readability Index (ARI) readability formula for English, and the Arabic ARI (AARI) readability formula for Arabic, both discussed at length by Al Tamimi et al. (2014).
- F[9] Morphemes - approximated by counting proclitics + enclitics + stem for any given token, first explored by Cavalli-Sforza et al. (2014) and Forsyth (2014), further tested by Saddiki et al. (2015) and Nassiri et al. (2017).
- All features in FeatMorphBase.LM follow the MADAMIRA POS34 tag set (Pasha et al., 2014).
- F[13], F[14] Open and closed class tokens are determined by POS34 tag.
- F[21], F[22] Marking passive voice as one of the few cases where diacritic marks are typically provided for disambiguation in otherwise undiacritized text intended for adult
readers of Arabic. It is also a frequently used indicator of difficult or poor readability in other languages (DuBay, 2007; Aluisio et al., 2010).

- F[23-28] Marking verb aspect (perfective, imperfective, imperative) as an indicator used with some success in other languages (Dell’Orletta et al., 2014a).
- F[29-36] Columbia Arabic Treebank (CATiB) tagset (Habash and Roth, 2009).
- F[63-74] A morpheme language model is generated with the higher granularity Morph-POS tagset (illustrated in Figure 1) based on (Buckwalter, 2002).
- F[99-110] A lemma-POS mixed language model is generated with the lemma of open-class tokens and the POS (Habash et al., 2012) for closed-class tokens.
- F[111-122] A POS-based language model is generated with the CATiB POS tagset (Habash and Roth, 2009).
- F[123-134] A POS-based language model is generated with the extended CATiB POS tagset presented in (Marton et al., 2013).
- F[135-146] A dependency language model is generated on the CATiB dependency tags in F[29-36] to get different levels of dependency context information, the most salient one being dependency information for parent-child nodes in the parse tree.

4 Modeling Readability

We evaluate readability prediction as a classification problem on a large feature set for documents in two text corpora designed for L1 and L2 reading, and labelled with readability levels 1, 2, 3 and 4 in increasing difficulty.

4.1 L1 and L2 Data

We leverage the L1 leveled reading corpus built by Khalil et al. (2018) based on grades 1 through 12 of an Arabic school curriculum and a collection of adult-level fiction. The corpus was split across 4 levels of readability in increasing order of difficulty: level 1 (905 documents), level 2 (1,192 documents), level 3 (2,054 documents) and level 4 (18,089 documents). The first three levels are sourced from curricular texts, grades 1-4, 5-8 and 9-12. The fourth considerably larger level contains novels suitable for post-secondary readers.

For L2, we work with an augmented version of the corpus used by Forsyth (2014), Saddiki et al. (2015) and Nassiri et al. (2017). It is comprised of 576 documents, leveled according to the Interagency Language Roundtable (ILR) scale for foreign language proficiency.\(^1\) With documents in the L2 corpus averaging 250 words, the L1 corpus was split accordingly for better comparability in our experiments.

Both the L1 and L2 datasets underwent an 80-10-10 random stratified split over the four levels for training (80%), development (10%) and testing (10%). The L1 corpus, partially sourced from textbook material from three different subjects, was also split across the three subjects to ensure a balanced sample of all three: Arabic, Social Studies, Islamic Studies.

4.2 Feature Extraction

The datasets are first enriched with several layers of linguistic annotation (e.g. Fig. 1) in preparation for feature extraction. Then, both raw text and annotations from the training set are used to build LMs for each of the 4 levels of readability (Table 3) with the SRILM toolkit (Stolcke et al., 2002). At this point, we begin extracting features from the various configurations of annotation and language models we generated:

- \textsc{Feat} \textsubscript{Raw Base.LM} features are extracted directly from the raw text, e.g. total number of characters in a document.
- \textsc{Feat} \textsubscript{Morph Base.LM} text is annotated with morphological, lexical and morpho-syntactic information using the MADAMIRA tool (Pasha et al., 2014) for morphological disambiguation.
- \textsc{Feat} \textsubscript{Syn Base.LM} text is annotated with syntactic parsing information using the Camel-Parser tool (Shahrour et al., 2016).

All \textsc{Feat} \textsubscript{Raw Morph Syn} features are obtained from computing occurrences, averages and other ratios over: raw text (\textsc{Feat} \textsubscript{Raw Base}); lemmatization, tokenization and morpho-syntactic annotation (\textsc{Feat} \textsubscript{Morph Base}); syntactic parsing annotation (\textsc{Feat} \textsubscript{Syn Base}). All \textsc{Feat} \textsubscript{LM} features

\(^1\)The scale goes from 0 (no proficiency) to 5 (native or bilingual proficiency) with + designation for intermediate levels, for further details http://www.govtilr.org/skills/ILRscale1.htm
are obtained from computing perplexity scores per document over the LMs generated using either raw text or text annotation (lemmas, POS, etc).

In total, there were 146 features extracted for each document. We perform three main experiments, described next, to determine their efficacy in the classification task for L1 and L2.

4.3 Experiment Setup
First, we build classifiers on the full feature set $FEAT_{Base,LM}$ to determine best performance for L1 and L2. All classification experiments are carried out within the WEKA environment (Hall et al., 2009). We test classification algorithms used with some success in previous work ($D.Tree$ decision tree, $Rnd.F$ random forest, $kNN$ k-nearest-neighbour, $SVM$ support vector machine). We include two baseline classifiers for reference: $zeroR$ (a simple classifier predicting the majority class for all instances) and $oneR$ (a 1-rule classifier using the feature with least error to predict the correct class).

Then, we test the performance of the feature subsets to assess the predictive power of different feature configurations for L1 and L2. We perform feature selection in two ways:

- Manually, following the categorization we defined in Table 2 and resulting in 12 combinations of feature sets to be tested: feature subsets (i, j) with i in {Raw, Morph, Syn} and j in {Base, LM} with $FEAT_{Raw,Base,LM}$ as the performance baseline for evaluating all feature subsets; composite subsets (i) with i in {Raw, Morph, Syn} or (j) in {Base, LM}; and finally the full feature set $FEAT_{Raw,Morph,Syn,LM,LM_1}$.

- Automatic feature selection using correlation-based feature selection (CFS) $FEAT_{Correl,Base,LM}$ implemented as CfsSubsetEval in WEKA with a BestFirst backward search through the feature space (Hall, 1999).

Finally, we experiment with the potential of using L1 $FEAT_{Raw,Morph,Syn,LM}$ to improve L2 readability predictions. First, we calculate perplexity scores for L2 documents using L1 LMs. We add these perplexity scores as features to the original L2 feature set, bringing the total set size to 254 features. Then, using this $FEAT_{Raw,Morph,Syn,LM,LM_1}$ feature set, we: (1) rerun the classifier performance experiment to see if any overall performance improvement is achieved; (2) run CFS feature selection on the L1-based LM subset to examine which features correlate the most with L2 readability classes. All experiments are reported in terms of F-score in addition to % Accuracy and F-score to give a better sense of prediction performance while accounting for class imbalance in the corpus.

5 Results and Discussion
In this section we present and discuss the results of experiments previously described in Section 5.3, which we organize as follows: results to optimize for classifier choice, results to optimize for features choice, and finally results on leveraging L1-based features for L2 readability prediction.

5.1 Classifier Choice Optimization
The classification results in Table 4 show that SVM performs best on overall accuracy for both L1 and L2 predictions. For L1, SVM achieves error reduction of 76% to the zeroR baseline, 64% to the oneR baseline, while outperforming other classifiers from the literature by varying degrees. Performance over the 4 levels of readability, measured in precision, recall and F-score, is as follows:

- **Precision:** Level 1 (78.3%), Level 2 (81.8%), Level 3 (89.4%) and Level 4 (97.5%)
- **Recall:** Level 1 (78.8%), Level 2 (68.9%), Level 3 (81.7%) and Level 4 (100%)
- **F-score:** Level 1 (78.5%), Level 2 (74.8%), Level 3 (85.4%) and Level 4 (98.7%)

Taking a closer look at misclassified documents, mostly from Levels 1, 2 and 3, we find the ma-

---

Table 3: Descriptive corpus statistics for our L1 and L2 data.

| Level | Source | Docs | Tokens |
|-------|--------|------|--------|
| 1     | K12 grades 1-4 (textbooks) | 1,230 | 297,772 |
| 2     | K12 grades 5-8 (textbooks) | 1,683 | 412,942 |
| 3     | K12 grades 9-12 (textbooks) | 2,553 | 628,978 |
| 4     | Original literary texts (novels) | 22,222 | 5,594,310 |

| Level | Source | Docs | Tokens |
|-------|--------|------|--------|
| 1     | 0 or 0+ (No proficiency) | 31 | 2,462 |
| 2     | 1 or 1+ (Elementary proficiency) | 177 | 40,816 |
| 3     | 2 or 2+ (Limited working proficiency) | 290 | 105,277 |
| 4     | 3 or 3+ (Professional working proficiency) | 78 | 37,570 |

| Level | Source | Docs | Tokens |
|-------|--------|------|--------|
| 1     | 0 or 0+ (No proficiency) | 31 | 2,462 |
| 2     | 1 or 1+ (Elementary proficiency) | 177 | 40,816 |
| 3     | 2 or 2+ (Limited working proficiency) | 290 | 105,277 |
| 4     | 3 or 3+ (Professional working proficiency) | 78 | 37,570 |
Table 4: Comparison of different classifiers using the full feature set $F_{EAT}$ for L1 (left) and L2 (right). Baseline performance is that of classifiers ZeroR and OneR. Performance is reported in terms of Accuracy (%) and F1-score (%) averaged over the 4 classification levels.

| Feature Subset | L1 SVM Classifier | L2 SVM Classifier |
|----------------|-------------------|-------------------|
| $F_{EAT}$ Base | Accuracy | Average F1 | Accuracy | Average F1 |
| ZeroR          | 79.9  | 21.9  | 50.0  | 16.7  |
| OneR           | 85.4  | 52.1  | 34.5  | 24.4  |
| D.Tree (C=0.25, M=12) | 72.2  | 50.4  | 31.0  | 21.7  |
| Rndm Frst (I=500) | 94.6  | 83.6  | 50.0  | 55.0  |
| kNN (k=9)    | 93.8  | 80.4  | 67.2  | 61.1  |
| SVM (C=5.0, rbfKernel) | 94.8  | 84.4  | 72.4  | 60.5  |

Table 5: Comparison of different feature subsets using SVM Classifier for L1 (based on best performance results from Table 4). Baseline performance is that of subset $F_{EAT}$ Base. Performance is reported in terms of Accuracy (%) and F1-score (%) averaged over the 4 classification levels.

| Feature Subset | L1 SVM Classifier |
|----------------|-------------------|
| $F_{EAT}$ Base | Accuracy | Average F1 |
| ZeroR          | 94.8  | 84.4  |
| ZeroR          | 94.3  | 83.3  |
| ZeroR          | 93.8  | 81.6  |
| ZeroR          | 88.6  | 61.4  |
| ZeroR          | 87.2  | 50.5  |
| ZeroR          | 85.3  | 42.6  |
| ZeroR          | 83.4  | 40.7  |
| ZeroR          | 82.7  | 39.7  |
| ZeroR          | 82.0  | 37.3  |
| ZeroR          | 81.8  | 33.7  |
| ZeroR          | 79.3  | 28.1  |
| ZeroR          | 78.0  | 22.5  |

Table 6: Comparison of different feature subsets using SVM Classifier for L2 (based on best performance results from Table 4). Baseline performance is that of subset $F_{EAT}$ Base. Performance is reported in terms of Accuracy (%) and F1-score (%) averaged over the 4 classification levels.

We find that all misclassified documents are only off by 1 level and often due to the intermediate proficiency levels marked by a ‘+’ being too close in difficulty to the next level up (e.g. a ‘1+’ proficiency document misclassified as ‘2’ according to the prevalence of more excerpts of original literary texts, especially in the Preparatory grades, could help explain why Level 4 predictions were obtained for some documents. Level 3 classification errs predominantly towards Level 4, this is also a plausible outcome considering that Arabic textbooks delve further into literature and include much longer excerpts of original fiction, and keeping in mind that some works of fiction are plausibly accessible to readers nearing the end of their K12 education.

Results for L2 remain consistent with 45% and 58% error reduction to the zeroR and oneR baselines, respectively.

We find that all misclassified documents are only off by 1 level and often due to the intermediate proficiency levels marked by a ‘+’ being too close in difficulty to the next level up (e.g. a ‘1+’ proficiency document misclassified as ‘2’ according to the
Table 7: L2 results with different classifiers on FEAT. **Comparison of different classifiers using the augmented feature set FEAT** for L2 (L2 features + L1 LM features). Baseline performance is that of classifiers ZeroR and OneR. Performance is reported in terms of Accuracy (%) and F1-score averaged over the 4 classification levels.

| Classifiers | L2 Accuracy | L2 F1 | L2 Accuracy | L2 F1 |
|-------------|-------------|-------|-------------|-------|
| ZeroR       | 50.0        | 16.7  | 50.0        | 16.7  |
| OneR        | 34.5        | 24.4  | 34.5        | 24.4  |
| D.Tree      | 31.0        | 21.7  | 31.0        | 21.7  |
| R.Forest    | 50.0        | 55.0  | 72.4        | 67.9  |
| KNN         | 67.2        | 61.1  | 74.1        | 66.2  |
| SVM         | 72.4        | 60.5  | 72.4        | 60.5  |

Baseline. All features are LM-based, with 50% of them extracted from raw text, ideal for low-cost performance with minimal NLP effort. This can be useful in lightweight web-based readability tools. We also noted with interest an 80%-20% split into vocabulary-based and syntax-based features, suggesting that vocabulary plays a more dominant role in readability than grammar.

### 5.3 L1-based Features for L2 Readability

Table 7 presents the results of augmenting L2 with L1 LM-based features. Adding L1 features to the L2 feature set did not degrade performance for any of the classifiers. While D.Tree and SVM classification did not show any significant improvement, the L1 features drastically improved prediction accuracy and F-score for Random Forest (Accuracy: 45% error reduction, F-score: 28.6% error reduction) and kNN (Accuracy: 3% error reduction, F-score: 13% error reduction) classification.

Looking into LM-based L1 features that correlate the most with L2 readability levels, we find that the most predictive of these features are mostly based on L1 readability levels 1 and 4, and distributed among raw character features, word features (raw and lemma), POS features, and parsing dependency features. Results from L2 using L1 encourage further exploration of L1 feature use in L2 readability prediction. It is worthwhile to explore the performance of classifying L1 documents on an L2 scale validated by expert judgment. Given the considerably smaller size of L2 resources in comparison with L1, we can potentially mine L1 for L2-readable material, thereby increasing the pool of texts available to L2 readers.
6 Conclusion and Future Work

We have presented the largest and most in-depth computational readability study for Arabic to date. We studied a wide set of features with varying depths from shallow words to syntactic trees for both L1 and L2 readability tasks. Our best L1 Readability accuracy result is 94.8% (75% error reduction from a commonly used baseline). The comparable results for L2 are 72.4% (45% error reduction). We demonstrated the added value of using L1 features for L2 readability prediction by increasing the L2 accuracy to 74.1% (an additional 6% error reduction).

The next step in improving model robustness and performance would be to address the dataset imbalance among the four levels for both L1 and L2 by adjusting sampling (He and Garcia, 2009). We are also considering a cost-sensitive prediction model: for instance, by assigning different costs to misclassification scenarios, we can penalize the model more heavily for errors in sparser levels.

In the future, we plan to employ our best results in the development of online tools to support an effort for text simplification for pedagogical purposes. Going forward in this direction, we expect to widen our range to include different levels of document granularity: 500-word to 1K-word size documents, as well as sentence-level readability (Dell’Orletta et al., 2014b).

References

Hend S Al-Khalifa and Amani A Al-Ajlan. 2010. Automatic readability measurements of the Arabic text: An exploratory study. Arabian Journal for Science and Engineering, 35(2 C):103–124.

Muhammed Al Khalil, Nizar Habash, and Hind Saddiki. 2017. Simplification of Arabic masterpieces for extensive reading: A project overview. Procedia Computer Science, 117:192–198.

Abdel Karim Al Tamimi, Manar Jaradat, Nuha Al-Jarrah, and Sahar Ghanem. 2014. AARI: automatic Arabic readability index. Int. Arab J. Inf. Technol., 11(4):370–378.

Sandra Aluisio, Lucia Specia, Caroline Gasperin, and Carolina Scarton. 2010. Readability assessment for text simplification. In Proceedings of the NAACL HLT 2010 Fifth Workshop on Innovative Use of NLP for Building Educational Applications, pages 1–9. Association for Computational Linguistics.

Lisa Beinborn, Torsten Zesch, and Iryna Gurevych. 2012. Towards fine-grained readability measures for self-directed language learning. In Proceedings of the SLTC 2012 workshop on NLP for CALL; Land; 25th October; 2012, 080, pages 11–19. Linköping University Electronic Press.

Tim Buckwalter. 2002. Buckwalter Arabic Morphological Analyzer Version 1.0. Linguistic Data Consortium, University of Pennsylvania, 2002. LDC Catalog No.: LDC2002L49.

Violetta Cavalli-Sforza, Mariam El Mezouar, and Hind Saddiki. 2014. Matching an Arabic text to a learners’ curriculum. In Proc. 5th Int. Conf. on Arabic Language Processing (CITALA), Oujda, Morocco, pages 79–88.

Kevyn Collins-Thompson. 2014. Computational assessment of text readability: A survey of current and future research. ITL-International Journal of Applied Linguistics, 165(2):97–135.

Kevyn Collins-Thompson and Jamie Callan. 2005. Predicting reading difficulty with statistical language models. Journal of the Association for Information Science and Technology, 56(13):1448–1462.

Felice Dell’Orletta, Simonetta Montemagni, and Giulia Venturi. 2014a. Assessing document and sentence readability in less resourced languages and across textual genres. ITL-International Journal of Applied Linguistics, 165(2):163–193.

Felice Dell’Orletta, Martijn Wieling, Giulia Venturi, Andrea Cimino, and Simonetta Montemagni. 2014b. Assessing the readability of sentences: Which corpora and features? In BEA@ ACL, pages 163–173.

William H DuBay. 2004. The Principles of Readability. Impact Information.

William H DuBay. 2007. Unlocking Language. Impact Information.

Mahmoud El-Haj and Paul Rayson. 2016. Osman: A novel Arabic readability metric. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016), Paris, France. European Language Resources Association (ELRA).

Lijun Feng, Noémie Elhadad, and Matt Huenerfauth. 2009. Cognitively motivated features for readability assessment. In Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics, pages 229–237. Association for Computational Linguistics.

Jonathan Forsyth. 2014. Automatic readability prediction for modern standard Arabic. In Proceedings of the First Workshop on Free/Open-Source Arabic Corpora and Corpora Processing Tools (LREC 2014), Reykjavik, Iceland.

Thomas François and Eleni Miltsakaki. 2012. Do nlp and machine learning improve traditional readability formulas? In Proceedings of the First Workshop on Predicting and Improving Text Readability for target reader populations, pages 49–57. Association for Computational Linguistics.

N. Habash, O. Rambow, and R. Roth. 2012. MADA+ TOKAN Manual. Technical report, Technical Report CCLS-12-01, Columbia University.
Nizar Habash and Ryan M Roth. 2009. CATiB: The Columbia Arabic Treebank. In Proceedings of the ACL-IJCNLP 2009 Conference Short Papers, pages 221–224. Association for Computational Linguistics.

Nizar Y Habash. 2010. Introduction to Arabic natural language processing, volume 3. Morgan & Claypool Publishers.

Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H Witten. 2009. The weka data mining software: an update. ACM SIGKDD explorations newsletter, 11(1):10–18.

Mark Andrew Hall. 1999. Correlation-based feature selection for machine learning. Ph.D. thesis, University of Waikato Hamilton.

Julia Hancke, Sowmya Vajjala, and Detmar Meurers. 2012. Readability classification for german using lexical, syntactic, and morphological features. In COLING, pages 1063–1080.

Haibo He and Eduardo A Garcia. 2009. Learning from imbalanced data. IEEE Transactions on knowledge and data engineering, 21(9):1263–1284.

Michael Heilman, Kevyn Collins-Thompson, Jamie Callan, and Maxine Eskenazi. 2007. Combining lexical and grammatical features to improve readability measures for first and second language texts. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference, pages 460–467.

Michael Heilman, Kevyn Collins-Thompson, and Maxine Eskenazi. 2008. An analysis of statistical models and features for reading difficulty prediction. In Proceedings of the Third Workshop on Innovative Use of NLP for Building Educational Applications, pages 71–79. Association for Computational Linguistics.

Muhamed Al Khalil, Hind Saddiki, Nizar Habash, and Latifa Alfalasi. 2018. A Leveled Reading Corpus of Modern Standard Arabic. In Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018).

Yuval Marton, Nizar Habash, and Owen Rambow. 2013. Dependency parsing of modern standard Arabic with lexical and inflectional features. Computational Linguistics, 39(1):161–194.

Naoual Nassiri, Abdelhak Lakhouaja, and Violetta Cavalli-Sforza. 2017. Modern standard Arabic readability prediction. In International Conference on Arabic Language Processing, pages 120–133. Springer.

Arfath Pasha, Mohamed Al-Badrashiny, Mona Diab, Ahmed El Kholy, Ramy Eskander, Nizar Habash, Manoj Pooleery, Owen Rambow, and Ryan M Roth. 2014. MADAMIRA: A Fast, Comprehensive Tool for Morphological Analysis and Disambiguation of Arabic. In Proceedings of the Language Resources and Evaluation Conference (LREC), Reykjavik, Iceland.

Hind Saddiki, Karim Bouzoubaa, and Violetta Cavalli-Sforza. 2015. Text readability for Arabic as a foreign language. In Proceedings of the IEEE/ACS 12th International Conference of Computer Systems and Applications (AICCSA), Marrakech, Morocco, pages 1–8. IEEE.

Anas Shahrour, Salam Khalifa, Dima Taji, and Nizar Habash. 2016. Camelparser: A system for arabic syntactic analysis and morphological disambiguation. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: System Demonstrations, pages 228–232.

Andreas Stolcke et al. 2002. Srilm-an extensible language modeling toolkit. In Interspeech, volume 2002, page 2002.