Improving Arabic Diacritization by Learning to Diacritize and Translate

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Abstract

We propose a novel multitask learning method for diacritization which trains a model to both diacritize and translate. Our method addresses data sparsity by exploiting large, readily available bitext corpora. Furthermore, translation requires implicit linguistic and semantic knowledge, which is helpful for resolving ambiguities in the diacritization task. We apply our method to the Penn Arabic Treebank and report a new state-of-the-art word error rate of 4.79%. We also conduct manual and automatic analysis to better understand our method and highlight some of the remaining challenges in diacritization.

1 Introduction

Arabic is typically written without short vowels and other pronunciation indication markers, collectively referred to as diacritics.\(^1\) A longstanding task in Natural Language Processing (NLP) is to take undiacritized text and add the diacritics, referred to as diacritization (see Figure 1). Diacritics not only indicate how to pronounce a word; they also resolve ambiguities in meaning between different words with the same (undiacritized) written form.

Diacritization has applications in Automatic Speech Recognition (ASR; Vergyri and Kirchhoff, 2004; Ananthakrishnan et al., 2005; Bradsy et al., 2009), Machine Translation (MT; Diab et al., 2007) morphological analysis (Habash et al., 2016), Arabic lexical recognition tests (Hamed and Zesch, 2018; Hamed, 2019), and homograph resolution (Alqahtani et al., 2019a).

Diacritization is the dominant source of errors in Arabic grapheme to phoneme conversion (Ali et al., 2020), a crucial component in Text-to-Speech (TTS). With the rise of personal digital assistants with TTS capabilities, there is a clear need for improved automatic diacritization methods.

We focus on Modern Standard Arabic (MSA), a standardized dialect of Arabic used in most academic, legal, and news publications, and an obvious choice for TTS systems. MSA is the 5th most spoken language in the world with about 274M speakers\(^2\) (Eberhard et al., 2021).

1.1 Challenge #1: Data Sparsity

Arabic is a morphologically rich language, where significant information concerning syntactic units and relations is expressed at word-level. For example, a word like فَسْقَينَاكِمْهُ is roughly translated to: ‘and we gave it to you to drink.’ This fact results in Arabic having a large vocabulary (by way of example, the number of unique, undiacritized words in the Ara-

\(^1\)Notable exceptions include the Quran and many children’s books.

\(^2\)“Speaker” is a bit of a misnomer: Most Arabic speakers can understand MSA but would not typically produce it.
bic bible from Christodouloupoulos and Steedman (2015) is about 4.38x larger than the number of unique, lower-cased words in the English equivalent.) Finally, high-quality diacritized datasets tend to be quite small: The Penn Arabic Treebank (PATB) training subset used in this work is only 15,789 lines, and data available in other dialects can be substantially smaller. These factors result in diacritized Arabic being very data sparse, with diacritics models typically needing to produce a large number of unseen words.

1.2 Challenge #2: Ambiguity

Arabic can express gender (male, female), number (singular, dual, plural), case (nominative, accusative, genitive), aspect (perfect, imperfect), voice (active, passive) and mood (indicative, imperative, subjunctive) at the word level, and distinctions are often conveyed using only diacritics. This results in undiacritized Arabic having a huge number of homographs; Debili et al. (2002) report an average of 11.6 possible diacritizations for each undiacritized word in Arabic. These homographs must be resolved by a diacritics model in order to correctly diacritize Arabic text.

1.3 Overview of Proposed Method

We propose a novel Multitask Learning (MTL; Caruana, 1997) based approach to diacritization. Specifically, we propose augmenting diacritics training data with bitext in order to train a model to both diacritize Arabic and translate into and out of Arabic.

Our approach addresses data sparsity by substantially increasing the amount of training data seen by the model, since it enables the use of large, readily available MT datasets (i.e. bitext). In our experiments on the PATB, adding bitext increases training data from 502k to 138M (non-unique) Arabic words, and decreases the Out-of-Vocabulary (OOV) rate from 7.33% to 1.14%. In contrast, prior MTL work in diacritization has used hand-curated features such as parts of speech, gender, and case (see §2.1), severely limiting both the amount of available data and the applicability to languages without such resources.

Our approach also addresses ambiguity, since task of translation requires (implicit) semantic and linguistic knowledge. Training on bitext injects semantic and linguistic knowledge into the model which is helpful for resolving ambiguities in diacritization (see Table 1).

These factors contribute to our method achieving a new State-of-the-Art (SOTA) Word Error Rate (WER) of 4.79% on the PATB, vs 7.49% for an equivalent baseline without MTL.

1.4 Main Contributions of This Work

The main contributions of this work are:

- We present a novel MTL approach for MSA diacritization, which does not require a morphological analyzer or specialized annotations, and thus is likely extensible to other languages and domains.
- We achieve a new SOTA WER of 4.79% on the PATB test set.
- We perform extensive automatic analysis of our method to see how it performs on various conditions including different parts of speech, genders, word frequencies, and sentence lengths.
- We perform detailed manual error analysis of our method, illustrating both issues in the PATB dataset as well as the remaining challenges in Arabic diacritization.

2 Related Word

2.1 Diacritization

Many works have explored using neural networks for Arabic diacritization (Zalmout and Habash, 2017, 2019; Alqahtani and Diab, 2019; Alqahtani et al., 2019b).

Alqahtani et al. (2020) and Zalmout and Habash (2020) both explored MTL regimes in which a model learns to predict Arabic diacritics simultaneously with other features in the PATB. Alqahtani et al. (2020) used additional features of syntactic diacritization, word segmentation, and Part of Speech (POS) tagging, and achieved a WER of 7.51%,\(^3\) while Zalmout and Habash (2020) used additional features of lemmas, aspect, case, gender, person, POS, number, mood, state, voice, enclitics, and proclitics, and a achieved a WER of 7.2%. By also adding an external morphological analyzer, they improved WER to 6.1%.

\(^3\)Unless stated otherwise, all word error rates in this work correspond to test set from the PATB data divisions proposed by Diab et al. (2013).
These works illustrate the potential of MTL, but they require additional hand-curated features. This limits both the datasets they can use (neither are able to take advantage of large additional datasets) and the languages they could be applied to.

### 2.1.1 Contextual Embeddings

Náplava et al. (2021) showed that contextual embeddings can result in substantial improvements in diacritization error rates in several languages, but unfortunately they did not report results on Arabic.

Qin et al. (2021) started with a strong baseline built on ZEN 2.0 (Song et al., 2021), an n-gram aware BERT variant. Their BERT-based baseline outperformed prior work on PATB. They then claimed even stronger results on PATB with two methods that incorporate multitask training with a second, auxiliary decoder trained to predict the diacritics produced by the Farasa morphological analyzer (Abdelali et al., 2016). We argue that their experimental setup was fundamentally flawed, since Farasa was trained on the PATB test set⁴ and can leak information about the test set to the model.⁵ They also reported results on the Tashkeela training/test data (Zerrouki and Balla, 2017; Fadel et al., 2019), which does not have a potential test set contamination problem, and found that their method under-performs a straightforward bidirectional LSTM,⁶ which supports the hypothesis that their strong PATB results are due to training on a derivative of the test set.

### 2.2 Character-level, Multilingual MT

Multilingual MT (Dong et al., 2015) has been shown to dramatically improve low-resource translation, including enabling transfer from higher resource language pairs to lower-resource language pairs (Zoph et al., 2016; Nguyen and Chiang, 2017; Neubig and Hu, 2018). In contrast, we encourage transfer from undiacritized Arabic to much lower-resource undiacritized Arabic.

Most MT systems operate at the subword level (Sennrich et al., 2016; Kudo and Richardson, 2018); however, such approaches could result in a diacritized word having little or no subword overlap with the undiacritized form of the same word. We instead train a character-level encoder-decoder model (Lee et al., 2017; Cherry et al., 2018), which has been shown to outperform subword-level models at diacritization (Alqahtani and Diab, 2019), to maximize the amount of shared representation between diacritized and undiacritized words.

### 3 Experiments

We train a character-level transformer encoder-decoder model on both the diacritics data and bitext. Our primary model performs diacritization results on the Tashkeela training/test set.

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| #  | Arabic Sentence | English Sentence | Voiced  | Pronunciation | Translation |
|----|----------------|-----------------|---------|---------------|-------------|
| 0  | علم السعودية أخضر وببغاء التنين | The flag of Saudi Arabia is green and white | یلام | یلام | flag |
| 1  | عَلَّمَ | I love space | یلما | یلما | science |
| 2  | علم ناصر أحمد السباحة | Nasser taught Ahmad how to swim | یلاما | یلاما | taught |

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⁴Farasa was trained on PATB parts 1, 2 and 3 in their entirety, and then tested on a separate collection of hand curated news articles (Abdelali et al., 2016).

⁵To understand how leakage from the test set can occur, consider the word علم (the star; female).  علم appears three times in the training data, once without diacritics (likely an error) and twice as علم (the star; genitive case). However, it appears 9 times in the test set, each time diacritized as علم (the star; without case ending). Farasa is trained on both the training and test data, so from Farasa’s perspective, علم is by far the most likely diacritization of علم. Thus when the model sees علم in training, Farasa can artificially bias the model toward producing the diacritic form in the test set, despite the form never appearing in the training data.

⁶Qin et al. (2021) claimed to achieve state-of-the-art performance on both datasets, but this is not supported by their results (see their Table 2, noting that bold does not denote the best system).
### Table 2: Diacritics considered in this work

| Name       | Form | Sound [IPA] |
|------------|------|-------------|
| Fatha      | ◁    | /a/         |
| Fathatan   | ◁    | /an/        |
| Kasra      | ◁    | /i/         |
| Kasratan   | ◁    | /in/        |
| Damma      | ◁    | /u/         |
| Dammatan   | ◁    | /un/        |
| Dagger Alif| ◁    | /aː/        |
| Maddah     | ◁    | /ʕaː/       |
| Shadda     | ◁    | Elongation (ː) |
| Sukun      | ◁    | None        |

| Ar-En | Ar-Es | Ar-Fr | Diacs |
|-------|-------|-------|-------|
| Global Voices | 0.9 | 0.9 | 0.5 | -   |
| CCAligned   | -    | 21.9 | 21.7 | -   |
| News Commentary | 5.0 | 5.0 | 4.3 | -   |
| United Nations | 20.7 | 19.9 | 19.5 | -   |
| WikiMatrix  | 15.0 | 1.7  | 1.6  | -   |
| PATB        | -    | -    | 0.5  | -   |
| Total       | 40.8 | 48.4 | 47.1 | 0.5 |

Table 3: Size (millions of Arabic words) of training datasets used in this work. Note that total bitext is about 275x larger than diacritics data.

The computational complexity of Transformer layers is proportional to sequence length squared (Vaswani et al., 2017), so we do not in order to (1) split Unicode characters which contain both a non-diacritic and diacritic (e.g. the Unicode character for alif with maddah above (U+0622) is split into alif (U+0627) and maddah (U+0653)) and (2) normalize the order of characters (e.g. alif + high hamza + fatha and alif + fatha + high hamza both render as ا and are normalized to alif + high hamza + fatha). The diacritics considered in this work are shown in Table 2.

### 3.3 MT Data

We use Ar↔{En,Fr,Es} data from Wikimatrix (Schwenk et al., 2019), Global Voices,\(^8\) United Nations (Ziemski et al., 2016), and News-Commentary,\(^9\) and Ar↔{Fr,Es} data from CCAligned (El-Kishky et al., 2020), after joining on English urls. We filter out noisy sentence pairs using the scripts\(^{10}\) provided by Thompson and Post (2020) using more aggressive thresholds of min_laser_score=1.06, max_3gram_overlap=0.1 for the CCAligned data and using values from Thompson and Post (2020) otherwise. We limit each dataset to 1M lines per language pair, so that no single data source dominates training. Data size are shown in Table 3. We up-sample PATB by 20x when combining it with the bitext, since it is much smaller than the bitext.

Adding bitext significantly reduces the OOV rates of the model: see Table 4.

### 3.4 Long Sentence Handling

The computational complexity of Transformer layers is proportional to sequence length squared (Vaswani et al., 2017), so we do not

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\(^7\)The tendency of a multilingual MT models to paraphrase input has been noted (and exploited) by Tiedemann and Scherrer (2019) and Thompson and Post (2020).

\(^8\) [casmacat.eu/corpus/global-voices.html](casmacat.eu/corpus/global-voices.html)

\(^9\) [data.statmt.org/news-commentary/](data.statmt.org/news-commentary/)

\(^10\) [github.com/thompsonb/prism_bitext_filter](github.com/thompsonb/prism_bitext_filter)
| Training Data       | OOV Rate |       |       |
|---------------------|----------|-------|-------|
|                     | Untiacritized | Diacritized |
| PATB                | 7.33%    | 10.54%|
| PATB + Bitext       | 1.14%    | 9.56% |

Table 4: OOV rates (rate of seeing word in test that was not seen in train), for encoder (which sees words without diacritics) and decoder (which produces words with diacritics). The bitext brings down the OOV rate substantially for the Encoder. We were surprised that the decoder OOV rate went down by adding (undiacritized) bitext; manual inspection showed this was because some a small percentage words in PATB are missing diacritics (see also: §6).

want to train or run inference on arbitrarily long sequences of characters. Instead, we limit the maximum input and output sequence length to 600.

To diacritize a sentence with more than 300 input characters, we take overlapping windows of 300 characters with a step size of 100 characters. We predict diacritics independently for each window, and construct the diacritized output sentence using portions of each window that have at least 100 characters of context on the input. For the bitext data, we simply discard sentence pairs with greater than 600 input or output characters.

3.5 Models & Training

We train character-level Transformer (Vaswani et al., 2017) models in fairseq (Ott et al., 2019). Hyperparameters are tuned on the development set.

The (non-MTL) baseline has 6 encoder and decoder layers, encoder and decoder embedding dimensions of 1024, encoder and decoder feed-forward network embedding dimensions of 8192, and 16 heads. All embeddings are shared. We train with a learning rate of 0.0004, label smoothing of 0.1, dropout of 0.4 with no attention or activation dropout, and 40k characters per batch, for 50 epochs.

All MTL models have 6 encoder and decoder layers, encoder and decoder embedding dimensions of 1280, encoder and decoder feed-forward network embedding dimensions of 12288, and 20 heads. All embeddings are shared. We train with a learning rate of 0.0004, label smoothing of 0.1, dropout of 0.2 with attention and activation dropout each set to 0.1, and 40k characters per batch, for 20 epochs.

We select the best performing model for each run using dev WER.

4 Results

The word error rates for our method (main model, both ablation models, and baseline) are shown in Table 5, along with error rates reported by prior work. Our main model achieves 4.71% WER on the development set, a relative improvement of 22.8% over the previous best development set result from Zalmout and Habash (2020), who trained a multitask model on PATB features and incorporated a morphological analyzer. On the test set, it achieves 4.79% WER, a relative improvement of 18.8% over the best previous test set result from Qin et al. (2021), who trained a BERT-based model.11

Our ablation models also outperform all prior work, with the model trained on Ar→* bitext outperforming the model trained on *→Ar bitext, but neither perform as well as the main model trained on both Ar→* and *→Ar. See §5 for more detailed comparisons between the models trained in this work.

Finally, our baseline model (a character-based Transformer trained without bitext) slightly outperforms to prior models from Alqahtani et al. (2019b) and Alqahtani and Diab (2019), that also do not use MTL, morphological analyzers, or contextual embeddings.

5 Automatic Analysis

5.1 Case Endings

We compute the Diacritic Error Rate (DER) for all models trained in this work for several different settings: all characters (including whitespace, punctuation, and non-Arabic characters), Arabic characters, Arabic case endings, and Arabic characters excluding case endings: see Table 6. We use POS tags to determine which words in the test set have case endings.12 Comparing our main model to the

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11We exclude the experiments of Qin et al. (2021) which use Farasa in training, as Farasa was trained on the test set (see §2.1.1).

12Several prior works have reported DER of just the last character as a stand-in for case-ending DER However, this analysis is muddied by the fact that not all words in Arabic have case endings; in the PATB test set, for example, the POS tags indicate that only about 46.8% of words have them.
Table 5: Development and Test WER (lower is better) for our main system, ablation systems, and baseline, compared to recent work. Our main system outperforms all prior work, as do both ablation systems. †: We exclude the experiments of Qin et al. (2021) which use Farasa in training, as Farasa was trained on the test set (see §2.1.1). ‡: Mean of 5 runs with different random seeds.

|                | Multitask? | Morphological | Word | Dev | Test |
|----------------|------------|---------------|------|-----|------|
|                |            | Analyzer?     | Embeddings? | WER ↓ | WER ↓ |
| Alqahtani et al. (2019b) | No         | No            | No   | 8.20% |
| Alqahtani and Diab (2019)  | No         | No            | No   | 7.60% |
| Alqahtani et al. (2020)    | PATB Features | No           | fastText | 7.51% |
| Zalmout and Habash (2019)  | PATB Features | Train & Test  | fastText | 7.30% |
| Zalmout and Habash (2020)  | PATB Features | Train & Test  | fastText | 6.10% |
| Qin et al. (2021)†         | No         | No            | Zen 2.0 | 6.49% |
| This word (baseline)       | No         | No            | No   | 7.46% |
| This work (ablation)       | Translate *→Ar | No           | No   | 5.60% |
| This work (ablation)       | Translate Ar→* | No          | No   | 5.24% |
| This work                  | Translate *→Ar & Ar→* | No       | No   | 4.71% |

Table 6: Diacritic error rate for all characters (including whitespace and non-Arabic characters), Arabic characters only, Arabic case endings (CE), and Arabic characters excluding case endings (non-CE). We use POS tags to determine which words contain case endings.

|                | Baseline | Multitask Learning | Both |
|----------------|----------|--------------------|------|
|                | 2.34%    | 1.85%              | 1.17%|
| Arabic         | 2.97%    | 2.35%              | 1.94%|
| Arabic CE      | 6.90%    | 2.48%              | 3.61%|
| Arabic non-CE  | 2.48%    | 2.06%              | 1.73%|

5.2 WER vs Sentence Length

We show WER as a function of sentence length (in undiacritized characters) in Figure 2. We note that while both the *→Ar and Ar→* models tend to improve with sentence length, the improvement is much more pronounced for the Ar→* model. In other words, the Ar→* model is benefiting much more from increased context than the *→Ar model.

In conjunction with the DER results in §5.1, this indicates that training the model to translate out of Arabic is more helpful at injecting semantic and linguistic knowledge into the model to address ambiguity. The fact that the two translation directions are complementary suggests that training the model to translate into Arabic is addressing data sparsity issues in the model’s decoder, despite the mismatch between the bitext being undiacritized and the model needing to produce diacritized output.
Table 7: WER for male vs female pronouns, verbs, and nouns/adjectives with gendered suffixes. †: We include only suffixes which are explicitly marked in the PATB for gender, which tend to be female: see §5.3

|      | Male Count | Male WER | Female Count | Female WER | Bias |
|------|------------|----------|--------------|------------|------|
| Pronoun | 835 | 6.23% | 641 | 8.11% | 30.3% |
| Verb   | 3579 | 5.34% | 2083 | 6.39% | 19.6% |
| Suffix | 901† | 5.22% | 10222 | 5.71% | 9.5% |

5.3 Gender Bias

Gender bias has been noted in many aspects of NLP (Sun et al., 2019) but we are not aware of any prior work looking at gender bias in diacritization. We use the PATB POS tags to isolate three types of gendered words: pronouns, verbs, and suffixes. We use the term “suffix” to refer to nouns and adjectives that have a gendered suffix. Unsurprisingly, we find that the model is better at diacritizing male words than female words in all three cases (see Table 7), with words in the female categories being diacritized incorrectly 9.5%-30.3% more often than for their male equivalents.

We suspect that this bias is due at least in part to representation within the data: Male pronouns and verbs are 30% and 72% more common than their female counterparts, respectively. Counts of suffixes are complicated by the fact that that PATB only marks certain nouns and adjectives for gender (including those with taa marbuta (i), which tend to be female). By manual inspection, the remainder appear to be male; however, we were unable to confirm this in the annotation guidelines so we included only suffixes explicitly marked for gender.

5.4 WER vs POS

The PATB includes detailed POS tagging. We exploit this feature to examine how our model performs on different parts of speech: see Table 8. Note that the PATB has one or more POS tags per word, with about 2.19 tags per word on average in the test set. We do not attempt to split words into their respective parts, as we find cases where this is not straightforward. Instead, such words are counted multiple times. As an example، (the first) is both a determiner and cardinal adjective, and contributes to the WER of both.

For the parts of speech we consider that have at least 500 occurrences in the test set, the worst performing POS for the MTL model by far is proper nouns (count=5969) at 14.09% WER. This is followed by imperfect verbs (count=2598) at 7.89% WER, possessive pronouns (count=1609) at 6.60%, and adjectives (excluding cardinal and comparative) (count=6106) at 6.49%.

Comparative adjectives, which are relatively infrequent (count=264) also have a high WER of 9.95%, but the worst POS considered by far is the extremely infrequent (count=18) imperative verbs, with a WER of 72.22%. Imperative verbs illustrate the importance of domain; news data contains very few imperatives, and imperative verbs (like most words in Arabic) are often distinguished from other words by diacritics alone. For example, imperatives can often have the same form as perfective verbs as in continue, which can be imperative as in (he continued). We confirm via manual inspection that the majority of the imperative verb errors are in fact homograph errors.

5.5 WER vs Word Frequency

MTL improves learning across all word frequencies: see Table 9. The biggest improvements are seen for words seen once and 2-4 times in training, with relative improvements of 43.6% and 45.5%, respectively.

6 Manual Analysis

We manually annotate all differences between our model prediction and the gold test set for a randomly selected 20% of the 1246 sentences in the test set that contain at least one disagreement.

We find that approximately 66% of the disagreements between the gold test set and the model are the result of model errors, which we denote as “true errors.” The majority of these errors are due to case markings being either incorrect (38.6% of all true errors) or missing (16.5% of all true errors), while the rest of the word is correct.

However, we find that the model is actually correct in approximately 34% of disagreements between the model output and the gold refer-
while the other had no diacritic, or one having diacritic variations which did not change the meaning of the sentence in any way (e.g. 

ويَكْشِفُ (my book); كَأَثْكَرَ (your book; fem)

Finally, only 4.2% of false errors were cases where the input to the model is not a real word, making the correct output undefined. A very small number of words (3.2% of false errors) had trivial diacritic variations (e.g. one having a sukun while the other had no diacritic, or one having a fatha before an alif while the other did not). 10.2% of the false errors were the result of valid variations which did not change the meaning of the sentence in any way (e.g. يَكْتُمَّ vs يَكْتُمَّ and الدُّوْلِيَّ vs الدُوْليَّ). Finally, only 4.2% of false errors were the result of valid variations that changed the meaning of the sentence in some way while still resulting in a plausible meaning. Our manual analysis suggests that the true WER of our MTL model is approximately 3.15%.

### 7 Conclusion

We demonstrate that training a diacritics model to both diacritize and translate substantially outperforms a model trained on the diacritization task alone. Adding translation data substantially increases the amount of training data seen by the model, addressing data sparsity issues in diacritization. The translation task also injects semantic and linguistic knowledge into the model, helping the model resolve ambiguities in diacritization.

Our method achieves a new state-of-the-art word error rate of 4.79% on the Penn Arabic Treebank datasets, using the standard data splits of Diab et al. (2013). Manual analysis of the errors indicates the true error rate is actually around 3.15%, after accounting for errors in the test set and plausible variations between the model output and test set.

Finally, our manual and automatic analysis points to several remaining challenges in Arabic diacritization, including proper nouns, female word forms, and case endings.

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| Noun: Proper | Baseline WER | MTL WER | Rel. imprv. | Examples |
|-------------|-------------|---------|-------------|----------|
| 5969        | 18.24%      | 14.09%  | 22.8%       | (Mary); أحمد (Ahmed) |
| 1609        | 3.29%       | 2.11%   | 35.8%       | (ten); (four) |
| 451         | 10.42%      | 5.32%   | 48.9%       | (any; fem); (some) |
| 22795       | 8.43%       | 5.03%   | 40.3%       | (day); (small country) |

| Pronoun: Possessive | Baseline WER | MTL WER | Rel. imprv. | Examples |
|---------------------|-------------|---------|-------------|----------|
| 1681                | 11.42%      | 6.60%   | 42.2%       | (my book); (your book; fem) |

| Pronoun: Demonstrative | Baseline WER | MTL WER | Rel. imprv. | Examples |
|------------------------|-------------|---------|-------------|----------|
| 601                    | 0.00%       | 0.17%   | 50.0%       | (this; male singular); (these, fem dual) |

| Pronoun: Other | Baseline WER | MTL WER | Rel. imprv. | Examples |
|---------------|-------------|---------|-------------|----------|
| 1154          | 1.04%       | 0.52%   | 50.0%       | (she saw me); (you; male singular) |

| Verb: Inflected, Perfect | Baseline WER | MTL WER | Rel. imprv. | Examples |
|--------------------------|-------------|---------|-------------|----------|
| 3273                     | 9.53%       | 4.89%   | 48.7%       | (he went); (it was accepted) |

| Verb: Inflected, Imperfect | Baseline WER | MTL WER | Rel. imprv. | Examples |
|----------------------------|-------------|---------|-------------|----------|
| 2598                      | 13.55%      | 7.89%   | 41.8%       | (he goes); (it is accepted) |

| Verb: Inflected, Imperative | Baseline WER | MTL WER | Rel. imprv. | Examples |
|-----------------------------|-------------|---------|-------------|----------|
| 18                         | 83.33%      | 72.22%  | 13.3%       | (go; male); (stop; fem) |

| Adverb | Baseline WER | MTL WER | Rel. imprv. | Examples |
|--------|-------------|---------|-------------|----------|
| 260    | 0.00%       | 0.38%   | 50.0%       | (when); (then) |

| Adjective: Cardinal | Baseline WER | MTL WER | Rel. imprv. | Examples |
|---------------------|-------------|---------|-------------|----------|
| 348                 | 7.18%       | 4.31%   | 40.0%       | (the 19th century); (the first) |

| Adjective: Comparative | Baseline WER | MTL WER | Rel. imprv. | Examples |
|------------------------|-------------|---------|-------------|----------|
| 264                    | 16.67%      | 9.85%   | 40.9%       | (more cautious); (the best) |

| Adjective: Other | Baseline WER | MTL WER | Rel. imprv. | Examples |
|-----------------|-------------|---------|-------------|----------|
| 6106            | 10.87%      | 6.49%   | 40.4%       | (historic); (Jewish) |

| Determiner | Baseline WER | MTL WER | Rel. imprv. | Examples |
|------------|-------------|---------|-------------|----------|
| 15337      | 8.72%       | 5.85%   | 32.9%       | (the Tunisian); (the day) |

Table 9: WER vs number of times a word occurs in PATB-train (ignoring diacritics), for all four models trained in this work.

Table 8: WER for our baseline and our main MTL model, for various parts of speech, and their associated count in the test set. Note: many words have more than one POS and contribute to 2+ categories (see §5.4).
References

Ahmed Abdelali, Kareem Darwish, Nadir Durrani, and Hamdy Mubarak. 2016. Farasa: A fast and furious segmenter for Arabic. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations, pages 11–16, San Diego, California. Association for Computational Linguistics.

Ikbel Hadj Ali, Zied Mnasri, and Zied Lachiri. 2020. Dnn-based grapheme-to-phoneme conversion for arabic text-to-speech synthesis. International Journal of Speech Technology, 23(3):569–584.

Sawsan Alqahtani, Hanan Aldarmaki, and Mona Diab. 2019a. Homograph disambiguation through selective diacritic restoration. In Proceedings of the Fourth Arabic Natural Language Processing Workshop, pages 49–59, Florence, Italy. Association for Computational Linguistics.

Sawsan Alqahtani and Mona Diab. 2019. Investigating input and output units in diacritic restoration. In 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA), pages 811–817.

Sawsan Alqahtani, Ajay Mishra, and Mona Diab. 2019b. Efficient convolutional neural networks for diacritic restoration. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1442–1448, Hong Kong, China. Association for Computational Linguistics.

Sawsan Alqahtani, Ajay Mishra, and Mona Diab. 2020. A multitask learning approach for diacritic restoration. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8238–8247, Online. Association for Computational Linguistics.

Sankaranarayanan Ananthakrishnan, Shrikanth Narayanan, and Srinivas Bangalore. 2005. Automatic diacritization of arabic transcripts for automatic speech recognition. In Proceedings of the 4th International Conference on Natural Language Processing, pages 47–54.

Fadi Biadsy, Nizar Habash, and Julia Hirschberg. 2009. Improving the Arabic pronunciation dictionary for phone and word recognition with linguistically-based pronunciation rules. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 397–405, Boulder, Colorado. Association for Computational Linguistics.

Rich Caruana, 1997. Multitask learning. Machine learning, 28(1):41–75.

Colin Cherry, George Foster, Ankur Bapna, Orhan Firat, and Wolfgang Macherey. 2018. Revisiting character-based neural machine translation with capacity and compression. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4295–4305, Brussels, Belgium. Association for Computational Linguistics.

Christos Christodoulopoulos and Mark Steedman. 2015. A massively parallel corpus: the bible in 100 languages. Language resources and evaluation, 49(2):375–395.

Fathi Debili, Hadhemi Achour, and Emma Souissi. 2002. La langue arabe et l’ordinateur: de l’étiquetage grammatical à la voyellation automatique. Correspondances, 71:10–28.

Mona Diab, Mahmoud Ghoneim, and Nizar Habash. 2007. Arabic diacritization in the context of statistical machine translation. In Proceedings of MT-Summit. Citeseer.

Mona Diab, Nizar Habash, Owen Rambow, and Ryan Roth. 2013. Ldc arabic treebanks and associated corpora: Data divisions manual. arXiv preprint arXiv:1309.5652.

Daxiang Dong, Hua Wu, Wei He, Dianhai Yu, and Haifeng Wang. 2015. Multi-task learning for multiple language translation. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1723–1732, Beijjing, China. Association for Computational Linguistics.

David M. Eberhard, Gary F. Simons, and Charles D. Fennig, editors. 2021. Ethnologue: Languages of the World, 24th edition. SIL International.

Ahmed El-Kishky, Vishrav Chaudhary, Francisco Guzmán, and Philipp Koehn. 2020. CCAligned: A massive collection of cross-lingual web-document pairs. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP 2020).

Ali Fadel, Ibhaeem Tuffaha, Mahmoud Al-Ayyoub, et al. 2019. Arabic text diacritization using deep neural networks. In 2019 2nd international conference on computer applications & information security (ICCAIS), pages 1–7. IEEE.

Nizar Habash, Anas Shahrouj, and Muhamed Al-Khalil. 2016. Exploiting Arabic diacritization for high quality automatic annotation. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 4298–4304, Portoroz, Slovenia. European Language Resources Association (ELRA).
Osama Hamed. 2019. Automatic diacritization as prerequisite towards the automatic generation of Arabic lexical recognition tests. In Proceedings of the 3rd International Conference on Natural Language and Speech Processing, pages 100–106, Trento, Italy. Association for Computational Linguistics.

Osama Hamed and Torsten Zesch. 2018. The role of diacritics in increasing the difficulty of Arabic lexical recognition tests. In Proceedings of the 7th workshop on NLP for Computer Assisted Language Learning, pages 23–31, Stockholm, Sweden. LiU Electronic Press.

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71, Brussels, Belgium. Association for Computational Linguistics.

Jason Lee, Kyunghyun Cho, and Thomas Hofmann. 2017. Fully character-level neural machine translation without explicit segmentation. Transactions of the Association for Computational Linguistics, 5:365–378.

Jakub Náplava, Milan Straka, and Jana Straková. 2021. Diacritics Restoration using BERT with Analysis on Czech language. The Prague Bulletin of Mathematical Linguistics, 116:27–42.

Graham Neubig and Junjie Hu. 2018. Rapid adaptation of neural machine translation to new languages. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 875–880, Brussels, Belgium. Association for Computational Linguistics.

Toan Q. Nguyen and David Chiang. 2017. Transfer learning across low-resource, related languages for neural machine translation. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 296–301, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations), pages 48–53, Minneapolis, Minnesota. Association for Computational Linguistics.

Han Qin, Guimin Chen, Yuanhe Tian, and Yan Song. 2021. Improving Arabic diacritization with regularized decoding and adversarial training. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 534–542, Online. Association for Computational Linguistics.

Holger Schwink, Vishray Chaudhary, Shuo Sun, Hongyu Gong, and Francisco Guzmán. 2019. Wikimatrix: Mining 135m parallel sentences in 1620 language pairs from wikipedia. CoRR, abs/1907.05791.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Yan Song, Tong Zhang, Yonggang Wang, and Kai-Fu Lee. 2021. Zen 2.0: Continue training and adaption for n-gram enhanced text encoders. arXiv preprint arXiv:2105.01279.

Tony Sun, Andrew Gaut, Shirlyn Tang, Yuxin Huang, Mai ElSherief, Jieyu Zhao, Diba Mirza, Elizabeth Belding, Kai-Wei Chang, and William Yang Wang. 2019. Mitigating gender bias in natural language processing: Literature review. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1630–1640, Florence, Italy. Association for Computational Linguistics.

Brian Thompson and Matt Post. 2020. Automatic machine translation evaluation in many languages via zero-shot paraphrasing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 90–121, Online. Association for Computational Linguistics.

Jörg Tiedemann and Yves Scherrer. 2019. Measuring semantic abstraction of multilingual NMT with paraphrase recognition and generation tasks. In Proceedings of the 3rd Workshop on Evaluating Vector Space Representations for NLP, pages 35–42, Minneapolis, USA. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, Advances in Neural Information Processing Systems 30, pages 5998–6008. Curran Associates, Inc.

Dimitra Vergyri and Katrin Kirchhoff. 2004. Automatic diacritization of Arabic for acoustic modeling in speech recognition. In Proceedings of the Workshop on Computational Approaches to Arabic Script-based Languages, pages 66–73, Geneva, Switzerland. COLING.
Nasser Zalmout and Nizar Habash. 2017. *Don’t throw those morphological analyzers away just yet: Neural morphological disambiguation for Arabic*. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 704–713, Copenhagen, Denmark. Association for Computational Linguistics.

Nasser Zalmout and Nizar Habash. 2019. *Adversarial multitask learning for joint multi-feature and multi-dialect morphological modeling*. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1775–1786, Florence, Italy. Association for Computational Linguistics.

Nasser Zalmout and Nizar Habash. 2020. *Joint diacritization, lemmatization, normalization, and fine-grained morphological tagging*. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8297–8307, Online. Association for Computational Linguistics.

Taha Zerrouki and Amar Balla. 2017. *Tashkeela: Novel corpus of arabic vocalized texts, data for auto-diacritization systems*. Data in brief, 11:147.

Michał Ziemski, Marcin Junczys-Dowmunt, and Bruno Pouliquen. 2016. *The United Nations parallel corpus v1.0*. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 3530–3534, Portorož, Slovenia. European Language Resources Association (ELRA).

Barret Zoph, Deniz Yuret, Jonathan May, and Kevin Knight. 2016. *Transfer learning for low-resource neural machine translation*. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1568–1575, Austin, Texas. Association for Computational Linguistics.