Persian Ezafe Recognition Using Transformers and Its Role in Part-Of-Speech Tagging

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Abstract

Ezafe is a grammatical particle in some Iranian languages that links two words together. Regardless of the important information it conveys, it is almost always not indicated in Persian script, resulting in mistakes in reading complex sentences and errors in natural language processing tasks. In this paper, we experiment with different machine learning methods to achieve state-of-the-art results in the task of ezafe recognition. Transformer-based methods, BERT and XLMRoBERTa, achieve the best results, the latter achieving 2.68% F1-score more than the previous state-of-the-art. We, moreover, use ezafe information to improve Persian part-of-speech tagging results and show that such information will not be useful to transformer-based methods and explain why that might be the case.

1 Introduction

Persian ezafe is an unstressed morpheme that appears on the end of the words, as -e after consonants and as -ye1 after vowels. This syntactic phenomenon links a head noun, head pronoun, head adjective, head preposition, or head adverb to their modifiers in a constituent called ‘ezafe construction’ (Nassajian et al., 2019). Whether a word in a sentence receives or does not receive ezafe might affect that sentence’s semantic and syntactic structures, as demonstrated in Examples 1a and 1b in Figure 1. There are some constructions in English that can be translated by ezafe construction in Persian. For instance, English ‘of’ has the same role as Persian ezafe to show the part-whole relation, the relationship of possession, or ‘s construction, and possessive pronouns followed by nouns showing genitive cases are mirrored by Persian ezafe (Karimi and Brame, 2012).

1The y is called an intrusive y and is an excrescence between two vowels for the ease of pronunciation.

This affix is always pronounced but almost always not written, which results in a high degree of ambiguity in reading and understanding Persian texts. It is hence considered as one of the most interesting issues in Persian linguistics and it has been discussed in details from phonological aspects (Ghomeshi, 1997), morphological aspects (Samvelian, 2006, 2007) and (Karimi and Brame, 2012), and syntactic aspects (Samiiian, 1994; Larson and Yamakido, 2008; Kahnemuyipour, 2006, 2014, 2016).

Nearly 22% of the Persian words have ezafe (Bijankhan et al., 2011), which shows the prevalence of this marker. Moreover, this construction also appears in other languages such as Hawramani (Holmberg and Odden, 2005), Zazaki (Larson and Yamakido, 2006; Toosarvandani and van Urk, 2014), Kurdish (Karimi, 2007) etc. Ezafe construction is also similar to idafa construction in Arabic and construct state in Hebrew (Habash, 2010; Karimi and Brame, 2012) and Zulu (Jones, 2018).

Ezafe recognition is the task of automatically labeling the words ending with ezafe, which is crucial for some tasks such as speech synthesis (Sheikhan et al., 1997; Bahaadini et al., 2011), as ezafe is always pronounced, but rarely written. Furthermore, as recognizing the positions of this marker in sentences helps determine phrase boundaries, it highly facilitates other natural language processing (NLP) tasks, such as tokenization (Ghayoomi and Momtazi, 2009), syntactic parsing (Sagot and Walther, 2010; Nourian et al., 2015), part-of-speech (POS) tagging (Hosseini Pozveh et al., 2016), and machine translation (Amtrup et al., 2000).

In this paper, we experiment with different methods to achieve the state-of-the-art results in the task of ezafe recognition. We then use the best of these methods to improve the results for the task of POS tagging. After establishing a baseline for this task, we provide the ezafe information to the POS tag-
Figure 1: An example of the role of ezafe in the syntactic and semantic structures.

Megerdoomian et al. (2000) use a rule-based method to design a Persian morphological analyzer. They define an ezafe feature to indicate the presence or absence of ezafe for each word based on its following words in a sentence. Another work is Müller and Ghayoomi (2010) that considers ezafe as a part of implemented head-driven phrase structure grammar (HPSG) to formalize Persian syntax and determine phrase boundaries. In addition, Nojoumian (2011) designs a Persian lexical diacritizer to insert short vowels within words in sentences using finite-state transducers (FST) to disambiguate words phonologically and semantically. They use a rule-based method to insert ezafe based on the context and the POS tags of the previous words.

As for the statistical approach, Koochari et al. (2006) employ classification and regression trees (CART) to predict the absence or presence of ezafe marker. They use features such as Persian morphosyntactic characteristics, the POS tags of the current word, two words before, and three words after the current word to train the model. Their train set contains approximately 70,000 words and the test corpus consists of 30,382 words. To evaluate the performance of the model, they use Kappa factor and the system prediction is 98.25% in the case of non-ezafe words and 88.85% in the case of words with ezafe. As another research, we can mention Asghari et al. (2014) that employs maximum entropy (ME) and conditional random fields (CRF) methods. They use the 10 million word Bijankhan
corpus (Bijankhan et al., 2011) and report an accuracy of 97.21% for the ME tagger and 97.83% for the CRF model with a window of size 5. They also utilize five Persian specific features in a hybrid settings with the models to achieve the highest accuracy of 98.04% with CRF.

Isapour et al. (2008) propose a hybrid method to determine ezafe positions using probabilistic context-free grammar (PCFG) and then consider the relations between the heads and their modifiers. The obtained accuracy is 93.29%, reportedly. The other work is Noferesti and Shamsfard (2014) that uses both a rule-based method and a genetic algorithm. At first, they apply 53 syntactic, morphological, and lexical rules to texts to determine words with ezafe. Then, the genetic algorithm is employed to recognize words with ezafe which have not been recognized at the previous step. To train and test the model, they use the 2.5 million word Bijankhan corpus (Bijankhan, 2004) and obtain an accuracy of 95.26%.

2.2 POS Tagging

Azimizadeh et al. (2008) use a trigram hidden Markov model trained on the 2.5 million word Bijankhan corpus. In order to evaluate, a variety of contexts such as humor, press reports, history, and romance are collected with 2000 words for each context. The average accuracy on different contexts is 95.11%. Mohseni and Minaei-Bidgoli (2010) also train a trigram Markov tagger on the 10 million word Bijankhan corpus. However, the lemma of each word is determined by a morphological analyzer at first and then a POS tag is assigned to the word. Using a 5-fold cross validation on the corpus, the obtained accuracy is 90.2%. Hosseini Pozveh et al. (2016) use ezafe feature for Persian POS tagging. They use the 2.5 million word Bijankhan corpus to train a recurrent neural network-based model, whose input vectors contain the left and the right tags of the current word plus the probability of ezafe occurrence in the adjacent words, achieving a precision of 94.7%. Rezai and Mosavi Miangah (2017) design a POS tool based on a rule-based method containing both morphological and syntactic rules. They use the tag set of the 2.5 million word Bijankhan corpus and their test set is a collection of more than 900 sentences of different types including medicine, literature, science, etc., and the obtained accuracy is 98.6%. Mohtaj et al. (2018) train two POS taggers on the 2.5 million word Bijankhan corpus, ME and CRF with different window sizes, the best results of which are 95% for both models with a window size of 5.

3 Methodology

We see both ezafe recognition and POS tagging as sequence labeling problems, i.e. mapping each input word to the corresponding class space of the task. For the ezafe recognition task, the class space size is two, 0 for words without and 1 for words with ezafe. The class space size for POS tagging task is 14, consisting of the coarse-grained POS tags in the 10 million word Bijankhan corpus. The results in Section 2.1 are unfortunately reported on different, and in most cases irreproducible, test sets, using accuracy as the performance measure (which is insufficient and unsuitable for the task), making the comparison difficult. We hence re-implemented the model that reports the highest accuracy on the largest test set and compare its results with ours.

3.1 Models

We experiment with three types of models: conditional random fields (CRF) (Lafferty et al., 2001), recurrent neural networks (RNN) (Rumelhart et al., 1986) with long short-term memory (LSTM) cells (Hochreiter and Schmidhuber, 1997) and convolutional neural networks (CNN), and transformer-based (Vaswani et al., 2017) models such as BERT (Devlin et al., 2018) and XLMRoBERTa (Conneau et al., 2019). These are the only transformer-based models pretrained on Persian data. To implement these models, we used sklearncrfsuite (Korobov, 2015; Okazaki, 2007), TensorFlow (Abadi et al., 2015), PyTorch (Paszke et al., 2019), and Hugging-Face’s Transformers (Wolf et al., 2019) libraries. The implementation details are as follows:

- CRF1: This is a re-implementation of Asghari et al. (2014)’s CRF model, as described in their paper. The input features were the focus word, 5 previous and 5 following words. We set the L1 and L2 regularization coefficients to 0.1 and the max iteration argument to 100.

- CRF2: This one is the same as CRF1, plus 8 other features: 1 to 3 first and last characters of the focus word to capture the morphological information and two Boolean features indicating if the focus word is the first/last word of the sentence.
• BLSTM: A single layer bidirectional LSTM with hidden state size of 256 plus a fully-connected network (FCN) for mapping to the class space. The input features were Persian word embedding vectors by FastText (Bojanowski et al., 2017) without subword information with embedding size of 300, which is proven to yield the highest performance in Persian language (Zahedi et al., 2018). The batch size was set to 16 for ezafe recognition and 4 for POS tagging, and learning rate to $1e^{-3}$. We applied a dropout of rate 0.5 on RNN’s output and used cross entropy as the loss function.

• BLSTM+CNN$^4$: The same as above, except for the input features of the BLSTM layer which also included extracted features from dynamic character embeddings of size 32 by two CNN layers with stride 1 and kernel size two, followed by two max pooling layers with pool size and stride 2. The first CNN layer had 64 filters and the second one 128. We also applied a dropout of rate 0.5 on CNN’s output. The character embeddings were initialized randomly and were trained with other parameters of the model.

• BERT and XLMRoBERTa: The main models plus a fully-connected network mapping to the tag space. The learning rate was set to $2e^{-5}$ and the batch size to 8. As for the pre-trained weights, for BERT, the multilingual cased model and for XLMRoBERTa, the base model were used. We have followed the recommended settings for sequence labeling, which is to calculate loss only on the first part of each tokenized word. Cross entropy was used as the loss function.

We used Adam (Kingma and Ba, 2014) for optimizing all the deep models above. For ezafe recognition, we train the models in a single-task setting. For POS tagging however, we train them in three different settings:

1. A single-task setting without ezafe information for all of the models.

2. A single-task setting with ezafe information in the input. The outputs of the best ezafe recognition model were added to the input of the POS tagging models: for CRFs as a Boolean feature, for BLSTM+CNN as input to CNN, and for BERT and XLMRoBERTa, in the input text. This setting was experimented with using all the models, except for CRF$_1$ and BLSTM.

3. A multi-task setting where the model learns POS tagging and ezafe recognition simultaneously, which means there is an FCN mapping to the POS class space and another one mapping to the ezafe class space. For the BLSTM+CNN model we used a batch size of 16 in this setting. The loss was calculated as the sum of the output losses of the two last fully-connected networks in this setting.

The hyper-parameters of the abovementioned models have been tuned by evaluating on the validation set to get the highest F$_1$-score. An Intel Xeon 2.30GHz CPU with 4 cores and a Tesla P100 GPU were used to train these models.

3.2 Performance Measure

Precision, recall, F$_1$-score, and accuracy were used to measure the performance of each model. In all the cases, the model was tested on the test set, using the checkpoint with the best F$_1$-score on the validation set. For the ezafe recognition task, we report the measures on the positive class and for the POS tagging task, we report the macro average.

4 Data

The 10 million word Bijankhan (Bijankhan et al., 2011) corpus was used in the experiments. We shuffled the corpus, as adjacent sentences might be excerpts from the same texts, with a random seed of 17 using Python’s random library. This corpus comprises different topics, including news articles, literary texts, scientific textbooks, informal dialogues, etc, which makes it a suitable corpus for our work. We used the first 10% of the corpus as test, the next 10% as validation, and the remaining 80% as train set. ~22% of the words have ezafe marker and ~78% of them do not, in each and all of the sets. Sentences with more than 512 words were set aside. Table 1 shows the number of sentences and tokens in each set.

Table 2 shows the frequency percentage of ezafe per POS in the corpus. Despite the previous claim that only nouns, adjectives and some prepositions

\footnote{Number of parameters are 3.4M and 9.0M for BLSTM and BLSTM+CNN, respectively.}
accept *ezafe* (Ghomeshi, 1997; Karimi and Brame, 2012; Kahnemuyipour, 2014), there is actually no simple categorization for POS’s that accept *ezafe* and those that do not, which you can see in Table 2 and is also backed by a more recent study on the matter (Nassajian et al., 2019). The last column in Table 2, $H$, is Shannon’s diversity index (Shannon, 1948; Spellerberg and Fedor, 2003), and is calculated as a diversity measure using Equation 1 for each POS tag. The higher the index is, the more diverse distribution the unique words have.

$$H = - \sum_{i=1}^{N} P(x_i) \ln P(x_i) \quad (1)$$

where $H$ is Shannon’s diversity index and $N$ is the number of unique words $x$ in each POS tag.

### 5 *Ezafe* Recognition

For *ezafe* recognition, we experimented with different sequence labeling techniques and report the performance of them. These techniques include CRF$_1$, CRF$_2$, BLSTM, BLSTM+CNN, BERT, and XLMRoBERTa, as discussed in Section 3.1.

#### 5.1 Results

Table 3 shows the results of all the models on the validation and test sets. It can be seen that transformer-based models outperform the other models by a huge margin. The best RNN-based model, BLSTM+CNN, outperforms the best CRF model, CRF$_2$, by 0.76% $F_1$-score. On the other hand the best transformer-based model, XLMRoBERTa, outperforms the best RNN by 1.78% $F_1$-score, and the best CRF by 2.54%. It should be noted that XLMRoBERTa outperforms the previous state-of-the-art, CRF$_1$, by 2.68% $F_1$-score. Figure 2 shows the precision, recall, and $F_1$-score on the test set. The transformer-based models also enjoy a more balanced precision and recall, which means a higher $F_1$-score. It is worth mentioning that XLMRoBERTa has a lower training time due to its much larger pretraining Persian data in comparison with BERT.

![Figure 2: *Ezafe* recognition precision, recall, and $F_1$-score, respectively from top to bottom, for all of the models on the test set.](image-url)

#### 5.2 Analysis

In comparison to CRFs and RNN-based methods, transformer-based models perform much better on more scarce language forms, such as literary texts and poetry, which means, given a test corpus with higher frequency of such texts, a much wider gap between the results is expected. We performed an error analysis specifically on XLMRoBERTa’s...
outputs to better understand its performance. We report ezafe $F_1$-score per POS tag in order of performance in Table 4.

| POS  | $Ezafe$ $F_1$ | POS  | $Ezafe$ $F_1$ |
|------|---------------|------|---------------|
| P    | 99.78%        | NUM  | 92.19%        |
| DET  | 98.60%        | CON  | 91.16%        |
| N    | 98.14%        | PRO  | 84.74%        |
| ADJ  | 96.61%        | MISC | 53.85%        |
| ADV  | 95.13%        | FW   | 30.43%        |

Table 4: Ezafe $F_1$-score per POS for XLMRoBERTa’s outputs on the test set. The average $F_1$-score is 84.06%.

- Preposition (P): With a relatively low diversity and a high frequency, according to Table 2, prepositions are the easiest one to label for the ezafe recognizing model. In addition, prepositions are exclusive in ezafe acceptance 93% of the time, which makes this POS quite easy. The most prevalent error in this POS is the model mistaking the preposition dar “in” with the noun dar “door”, the second of which accepting ezafe almost half of the time.

- Determiners (DET): They are easy to recognize partly due to their low diversity. In this POS, the model fails to recognize ezafe specifically when the word shares another POS in which it differs in ezafe acceptance, e.g. hadde’aksar “maximum” and bištär “mostly, most of”, which accept ezafe in DET role, but not in ADV.

- Nouns (N): Despite its high diversity, the model shows a high performance in detecting ezafe in this POS. This is probably due to its high frequency and high ezafe acceptance. Morphological information helps the most in this POS, as many nouns are derived or inflected forms of the existing words. The performance suffers from phrase boundaries detection, which results in false positives. The model also fails to recognize ezafe on low-frequency proper nouns, such as Shakespeare. Another common error in this POS is the combination of first and last names, which are usually joined using ezafe.

- Numbers (NUM): The errors in this POS comprise mainly the cardinal numbers, especially when written in digits. The main reason could be the scarcity of digits with ezafe. For instance, look at Example 3 (the error is in bold):

(3) *sál-e 1990-e milādī*  
year-ez. 1990-ez. Gregorian  
“year 1990 of the Gregorian calendar”

- Conjunctions (CON): It is quite rare for a conjunction to accept ezafe, which consequently causes error in ezafe recognition.

- Pronouns (PRO): PRO has a low ezafe acceptance rate and a low frequency, which makes it a difficult POS. Most of the errors in this POS occur for the emphatic pronoun xod “itself, themselves, etc.”, which receives ezafe, as opposed to its reflective role, which does not.

- Miscellaneous (MISC): Low ezafe acceptance and low frequency are the main reasons for
the errors in this POS. The errors mainly consist of Latin single letters in scientific texts. Look at Example 4, for instance (the error is in bold):

(4) $L$-$e$ be dast 'âmade
\hspace{1cm} L-$ez$ to hand come
the obtained [value of] L

- Foreign words (FW): With a very low frequency, very low ezafe acceptance rate, and a very high diversity, this POS is by far the most difficult one for the model. Additionally, FW usually appears in scientific and technical texts, which makes it harder for the model, as such texts contain considerable amount of specialized low frequency vocabulary. Examples of errors in this POS are 'DOS', ‘Word’, ‘TMA’, ‘off’, ‘TWTA’, etc.

As discussed above, errors are most prevalently caused by model’s mistaking phrase boundaries and homographs that have different syntactic roles and/or ezafe acceptance criteria. While conducting the error analysis, we discovered considerable amounts of errors in Bijankhan corpus, which motivated us to correct the ezafe labels of a part of the test corpus and measure the performance again. We therefore asked two annotators to re-annotate ezafe labels of the first 500 sentences of the test corpus in parallel, and a third annotator’s opinion where there is a disagreement. You can see the results of the best model, XLMRoBERTa, on the first 500 sentences of the test set, before and after ezafe label correction in Table 5. These 500 sentences contain 14,934 words, 3,373 of them with ezafe, based on Bijankhan labels.

| Test Corpus | Precision | Recall | F$_1$-score |
|-------------|-----------|--------|-------------|
| Bijankhan   | 0.9691    | 0.9851 | 0.9770      |
| Corrected   | 0.9838    | 0.9897 | 0.9867      |

Table 5: XLMRoBERTa’s precision, recall, and F$_1$-score on the first 500 sentences of the test set, before and after ezafe label correction.

Correcting ezafe labels resulted in 0.97% increase in F$_1$-score on the abovementioned part of the test corpus. The same correction for all of the test corpus might result in a near 99% F$_1$-score for XLMRoBERTa model. Transformer-based models perform remarkably even where there is a typo crucial to ezafe recognition, i.e. when the intrusive consonant ‘y’ is missed between an ending vowel and a (not-written) ezafe, for instance, diskhâ-y[e] “disks” and be’ezâ-y[e] “for”.

## 6 POS Tagging

For the task of POS tagging, we experimented with CRF$_1$, CRF$_2$, BLSTM+CNN, BERT, and XLM-RoBERTa models in the single-task settings, multi-task settings with ezafe as the auxiliary task (except for CRFs), and also in a single-task settings with ezafe information in the input. For the last one, we added the ezafe output of XLMRoBERTa in Section 5 to the input text. In this section, we first explain the role of ezafe information in POS tagging, then we discuss the results of the POS tagging task and then, we analyse it.

### 6.1 The Role of Ezafe

Ezafe is a linker between words in nonverbal phrases. It is hence not used between phrases, which can be an indicator of phrase boundaries (Tabibzadeh, 2014). Compare Examples 5a and 5b, for instance. This means that ezafe information will help the model, and also humans, to better detect the phrase boundaries, which can be helpful in recognizing syntactic roles (Nourian et al., 2015).

(5) a. [pesar] [xôšâ] [’âmad] boy happy came
N ADV V
“The boy came happily”

b. [pesar-e xôšâl] [’âmad] boy-ez. happy came
N ADJ V
“The happy boy came”

Knowing ezafe also helps the model determine the POS of some homographs. Some examples are as follows. The information below is resulted from studying homographs based on their POSs in Bijankhan corpus.

- The ‘i’ suffix in Persian can be derivational or inflectional. When derivational, it is either a nominalizer or an adjectivizer and the derived form will accept ezafe. When inflectional, it is an indefinite marker and the inflected form will not accept ezafe. Some examples are kamyâbi “scarcity, rarity”, yêksân “sameness”, şegeft’ângizi “wonderfulness”, bimâri “illness”, ‘âspâzi “cooking”.
- Adverbized adjectives that are homonyms in both roles, accept ezafe only in their adje-
Table 6: POS tagging results (precision, recall, F1-score, and accuracy) on the validation and test sets using the single- and multi-task and enafe in the input settings. In each column, the best result(s) is/are in bold, the second best underlined, and the third best italicized. The last column shows the approximate training time in hours.

| Input | Model       | Prec.  | Recall | F1     | Acc.  | Prec.  | Recall | F1     | Acc.  | Approx. T.T. |
|-------|-------------|--------|--------|--------|-------|--------|--------|--------|-------|--------------|
| Single | CRF2 (baseline) | 0.9688 | 0.9380 | 0.9521 | 0.9832 | 0.9680 | 0.9373 | 0.9511 | 0.9831 | 0.8 h        |
|       | CRF2        | 0.9679 | 0.9530 | 0.9602 | 0.9854 | 0.9684 | 0.9514 | 0.9595 | 0.9854 | 0.9 h        |
|       | BLSTM+CNN   | 0.9680 | 0.9573 | 0.9626 | 0.9873 | 0.9677 | 0.9570 | 0.9623 | 0.9869 | 1.3 h        |
|       | BERT        | 0.9703 | 0.9719 | 0.9710 | 0.9899 | 0.9687 | 0.9716 | 0.9701 | 0.9895 | 1.4 h        |
|       | XLMRoBERTa  | 0.9700 | 0.9718 | 0.9708 | 0.9900 | 0.9706 | 0.9714 | 0.9709 | 0.9901 | 0.9 h        |
| Input | CRF2        | 0.9697 | 0.9563 | 0.9628 | 0.9859 | 0.9708 | 0.9555 | 0.9629 | 0.9859 | 1 h          |
|       | BLSTM+CNN   | 0.9724 | 0.9597 | 0.9660 | 0.9878 | 0.9731 | 0.9587 | 0.9658 | 0.9877 | 1.4 h        |
|       | BERT        | 0.9731 | 0.9694 | 0.9711 | 0.9897 | 0.9710 | 0.9690 | 0.9700 | 0.9897 | 1.5 h        |
|       | XLMRoBERTa  | 0.9730 | 0.9689 | 0.9709 | 0.9896 | 0.9714 | 0.9692 | 0.9703 | 0.9895 | 1 h          |
| Multi | BLSTM+CNN   | 0.9727 | 0.9569 | 0.9647 | 0.9875 | 0.9724 | 0.9565 | 0.9643 | 0.9872 | 1.4 h        |
|       | BERT        | 0.9735 | 0.9665 | 0.9699 | 0.9896 | 0.9728 | 0.9650 | 0.9688 | 0.9888 | 1.5 h        |
|       | XLMRoBERTa  | 0.9730 | 0.9665 | 0.9692 | 0.9887 | 0.9725 | 0.9648 | 0.9686 | 0.9884 | 1 h          |

Table 7: The change in POS tagging F1-scores for single-task, in the inputs, and multi-task settings, respectively from top to bottom, on the test set.

| POS | CRF2 | B.+C. | POS | CRF2 | B.+C. |
|-----|------|------|-----|------|------|
| IDEN | +2.80% | +2.99% | ADJ | +0.05% | +0.07% |
| FW   | +0.79% | +0.83% | P   | +0.03% | +0.06% |
| ADV  | +0.64% | +0.69% | N   | +0.03% | +0.03% |
| DET  | +0.13% | +0.16% | NUM | +0.02% | +0.02% |
| V    | +0.06% | +0.15% | CON | +0.01% | +0.00% |
| PRO  | +0.06% | +0.08% | DELM| +0.00% | +0.00% |
| MISC | +0.06% | +0.08% | PSTP| +0.00% | -0.01% |

6.2 Results

Table 6 shows the results of POS tagging on validation and test sets using single- and multi-task and enafe in the input settings. With the single-task settings, XLMRoBERTa and BERT outperform the other models and have almost equal performances. When enafe information is fed to the input, the precision of all the models increases while the recall has a more complex behavior. For CRF2 and BLSTM+CNN, it sees a slight increase, and for transformer-based models it sees a decrease of 0.3 to 0.4%. The F1-score of CRF2 model increases by 0.34% and BLSTM+CNN model by 0.27%. For BERT, it stays almost the same, and for XLMRoBERTa, it sees a decrease of 0.06%. Table 7 shows the change in F1-scores of each POS when enafe is fed with the input. As for the multi-task settings, the precision goes up and the recall and the F1-score come down for transformer-based and BLSTM-CNN models. Figure 3 shows POS tagging F1-scores for single-task, in the inputs, and multi-task settings, respectively from top to bottom, on the test set.

Figure 3: POS tagging F1-scores for single-task, input, and multi-task settings, respectively from top to bottom, on the test set.

Table 8 shows POS tagging F1-scores per POS on the test set for the single-task and enafe in the input settings for CRF2 and BLSTM+CNN models and for single-task settings for XLMRoBERTa model. You can see the increase in F1-score when enafe information is provided to the model. As there is no increase in XLMRoBERTa’s results when enafe information is provided, the results for this setting are not shown for this model.
As discussed in Subsection 6.1, we anticipated to see an increase in several POSs, including N, ADJ, ADV, DET, V, and IDEN. According to Table 8, the highest increase belongs to IDEN, FW, ADV with an average increase of ~2.75%, ~0.81%, and ~0.67%, respectively. The increase for V is 0.06% and for N, 0.03% for both models, and for DET, 0.13% and 0.08%, and for ADJ, 0.05% and 0.16% for CRF$_2$ and BLSTM+CNN, respectively.

As for the transformer-based models results, they do not seem to benefit from the ezafe information either in the input or as an auxiliary task. As the work on syntactic probing shows, attention heads in transformer-based models, specifically BERT, capture some dependency relation types (Htut et al., 2019). As ezafe is a more limited form of dependency (Nassajian et al., 2019), its information could be captured by the attention heads in such models. On the other hand, contextualized embeddings also seem to capture some syntactic relations (Tenney et al., 2019; Hewitt and Manning, 2019) which is another reason for such models’ high performance in capturing ezafe information.

All in all, it seems that transformer-based models already have captured the ezafe information owing to their architecture (attention heads), pretraining, contextual embeddings, and finally, being trained on the POS tagging task (which is related to the task of ezafe recognition, and that is why their performance does not enhance when such information is provided.

### Table 8: POS tagging F$_1$-scores per POS on the test set for CRF$_2$ and BLSTM+CNN (single-task and ezafe in the input) and for XLMRoBERTa (single-task).

| POS | CRF$_2$ Single Input | BLSTM+CNN Single Input | X.R. Single Input |
|-----|----------------------|------------------------|------------------|
| DELM | 0.9999 0.9999 | 1.0000 1.0000 | 1.0000 |
| PSTP | 0.9995 0.9995 | 0.9996 0.9995 | 0.9998 |
| NUM | 0.9964 0.9966 | 0.9974 0.9982 | 0.9969 |
| CON | 0.9949 0.9950 | 0.9964 0.9964 | 0.9968 |
| P | 0.9944 0.9947 | 0.9959 0.9961 | 0.9966 |
| V | 0.9943 0.9949 | 0.9958 0.9964 | 0.9965 |
| N | 0.9870 0.9873 | 0.9893 0.9896 | 0.9904 |
| PRO | 0.9711 0.9717 | 0.9788 0.9795 | 0.9835 |
| DET | 0.9661 0.9674 | 0.9705 0.9713 | 0.9784 |
| ADJ | 0.9519 0.9524 | 0.9539 0.9555 | 0.9635 |
| ADV | 0.9300 0.9364 | 0.9414 0.9483 | 0.9534 |
| MISC | 0.9117 0.9123 | 0.9127 0.9142 | 0.9375 |
| FW | 0.9046 0.9125 | 0.9036 0.9119 | 0.9337 |
| IDEN | 0.8318 0.8598 | 0.8375 0.8644 | 0.8656 |

7 Conclusion and Future Work

In this paper, we experimented with different models in the tasks of ezafe recognition and POS tagging and showed that transformer-based models outperform the other models by a wide margin. We also provided ezafe information to the POS tagging models and showed that while CRF and RNN-based models benefit from this information, transformer-based models do not. We suggest that this behavior is most probably due to (1) contextual representation, (2) pretrained weights which means a limited knowledge of syntactic relations between words, (3) the attention heads in these models, and (4) being trained on the POS task, which is related to ezafe recognition. An interesting direction for the future work would be to investigate the role of ezafe in transformer-based models in the tasks that such information would be helpful, such as dependency and shallow parsing.

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