Automatic Standardization of Colloquial Persian

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Abstract

The Iranian Persian language has two varieties: standard and colloquial. Most natural language processing tools for Persian assume that the text is in standard form: this assumption is wrong in many real applications especially web content. This paper describes a simple and effective standardization approach based on sequence-to-sequence translation. We design an algorithm for generating artificial parallel colloquial-to-standard data for learning a sequence-to-sequence model. Moreover, we annotate a publicly available evaluation data consisting of 1912 sentences from a diverse set of domains. Our intrinsic evaluation shows a higher BLEU score of 62.8 versus 61.7 compared to an off-the-shelf rule-based standardization model in which the original text has a BLEU score of 46.4. We also show that our model improves English-to-Persian machine translation in scenarios for which the training data is from colloquial Persian with 1.4 absolute BLEU score difference in the development data, and 0.8 in the test data.

1 Introduction

There has recently been a great deal of interest in developing natural language processing (NLP) datasets and models for the Persian language (e.g. (Bijankhan et al., 2011; Rasooli et al., 2013; Feely et al., 2014; Seraji, 2015; Nourian et al., 2015; Seraji et al., 2016; Mirzaei and Moloodi, 2016; Mirzaei and Safari, 2018; Pootsch et al., 2018; Mirzaei et al., 2020; Taher et al., 2020; Khashabi et al., 2020)). Despite impressive achievements, most of Persian NLP models assume that the text is written in the standard form. This assumption is practically not true (Solhju, 2019). This particular phenomenon is somewhat similar to dialectal variations in Arabic, but it is less diverse than what we observe in Arabic dialects. The general upshot is that many natural language processing systems for Persian might easily break when dealing with a mixture of colloquial and standard text. This is indeed an important issue given the surge in using social media and online contents.

The focus of this paper, similar to the majority of previous work, is on contemporary Iranian Persian. Persian is an Indo-European language with more than 100 million speakers across the world especially in Iran, Afghanistan, and Tajikistan (Windfuhr, 2009). Loosely speaking, Iranian Persian is used in two different but similar forms: standard and colloquial (Boyle, 1952; Shamsfard, 2011; Tabibzadeh, 2020). In some sense, this idiosyncratic phenomenon is a type of diglossia for which there exists a high variety of language used in formal writing, and a low variety used in spoken language (Jeremiás, 1984; Mahmoodi-Bakhtiari, 2018). What we refer here as colloquial Persian is a version of the spoken language that is mostly used in Tehran (capital of Iran). However, due to the national academic system and media, most people in Iran understand and use it in daily basis (Solhju, 2019).

Colloquial Persian has many broken words for which some of them invent their own morphology, and sometimes idiosyncratic syntactic order, and some new idioms (Tabibzadeh, 2020). It is diverse and appears in different shapes from merely standard syntax with some occasional broken words (as used in TV and radio news) to broken words with colloquial syntax. Depending on the formality of context and personal writing style, a colloquial sentence might have some few broken words and few other standard word forms: This is somewhat like code-switching between two varieties of the
same language instead of two distinct languages.

This paper proposes an automatic method for standardizing colloquial Persian text. The core idea behind our work is training a sequence-to-sequence translation model (Vaswani et al., 2017) that translates colloquial Persian to standard Persian. We believe that our approach is a more viable technique than merely applying some conversion rules for standardization. On the one hand, writing an extensive set of rules depending on different semantic contexts is cumbersome, if not impossible. On the other hand, using a sequence-to-sequence model facilitates leveraging pretrained language models such as masked language models (Devlin et al., 2019) trained on huge amount of monolingual texts. Our experiments also prove this point. Since there is no available parallel text between standard and colloquial Persian, we propose a random standard-to-colloquial conversion algorithm based on recent linguistic studies on common colloquial word forms in Persian literature (Bakhshizadeh Gashti and Tabibzadeh, 2019; Tabibzadeh, 2020).

Our contribution is three-fold: 1) We propose a novel method for training translation models from colloquial to standard Persian, and show improvements over an off-the-shelf rule-based model. Except a paper written in Persian with a simple n-gram approach (Armin and Shamsfard, 2011) and without any code or data release, we are not aware of any work on this topic; 2) We provide a publicly available manually annotated evaluation data for colloquial Persian with two types of standardization for which the first only concerns surface word forms, and the second considers making the text stylistically standard. This data consists of 1929 sentences from different genres including fiction, translated fiction, blog posts, public group chats, and comments in news websites; and 3) We show that our method improves English-to-Persian machine translation trained on colloquial Persian data.

2 Automatic Standardization and Evaluation

There are three core components of our research: 1) Modeling, 2) Training data, 3) Evaluation. This section briefly describes these three components.

2.1 Model

We model colloquial-to-standard text conversion as machine translation. The input to the system is a sequence of colloquial words \( \{ x_1 \ldots x_n \} \) and the output is a sequence of standard word forms \( \{ y_1 \ldots y_n \} \) where \( n \) and \( m \) are not necessarily equal. We train a standard neural machine translation model with attention (Vaswani et al., 2017) on a training data in which each colloquial sentence is accompanied by its standard version. Figure 1 shows examples of such training data. Neural machine translation uses sequence-to-sequence models with attention (Cho et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017) for which the likelihood of training data \( D = \{ (x^{(1)}, y^{(1)}) \ldots (x^{(|D|)}, y^{(|D|)}) \} \) is maximized by maximizing the log-likelihood of predicting each target word given its previous predicted words and source sequence:

\[
\mathcal{L}(D) = \sum_{i=1}^{|D|} \sum_{j=1}^{\left| y^{(i)} \right|} \log p(y_j^{(i)} | y_{k<j}^{(i)}, x^{(i)}; \theta)
\]

where \( \theta \) is a collection of parameters to be learned.

2.2 Training Data Generation

Since there is no parallel data to train a machine translation model, we define a set of rules to break standard forms into colloquial forms. In general, there are more than 300 rules, mostly inspired from Bakhshizadeh Gashti and Tabibzadeh (2019). Table 1 lists the main rules used in this work. These rules include changing vowels (e.g. \( a \rightarrow Ù æ \)), modifying verb forms (e.g. \( Ù beguyæm \rightarrow Ù begam \)), and other types of conversion listed by Bakhshizadeh Gashti and Tabibzadeh (2019).

Our conversion rules define a function \( f(x_i, x_{i+1}) \) in which depending on part-of-speech tag and the next word \( x_{i+1} \) form, a new word form \( y \) or a sequence of word forms are generated. Since we are not sure about the extent in which words are broken in text, we randomly skip some conversions with a probability of 0.1 in order to make the text look like a mix of colloquial and standard word forms. One advantage of this approach is that we can easily have a large amount of parallel text to train a neural machine translation model. Some real examples are shown in Figure 1. There are definitely many cases for which our

\[1\text{Available for download from } \text{https://github.com/rasoolims/Shekasteh}\]

\[2\text{The code for this rules is publicly available in } \text{https://github.com/rasoolims/PBreak.}\]
We collect data from different sources including comments on news websites, discussions on web forums, translated fiction, and dialogues in Persian fiction. Three native speaker linguists have annotated the data in which the development part (917 sentences) is annotated by the first annotator, and the test data (1012 sentences) is annotated by the other two annotators. For the sake of keeping sentences coherent, many sentences are actually multiple short sentences. Figure 2 shows the counts of sentences in different topics. As seen in the Figure, the distributions of the development and test datasets are intentionally very different.

### 3 Experiments

In this section we describe our experiments and results. In addition to intrinsic evaluation on our evaluation datasets, we use machine translation as an extrinsic task for which the training data only contains colloquial text while the test data contains standard text.

#### 3.1 Datasets and Tools

**Datasets:** We use the Wikipedia dump of Persian as standard text in addition to one million sentences from the Mizan corpus (Kashefi, 2018). We randomly break words and use this data as training data for standardization. Figure 1 shows a few examples of converted text to colloquial. For machine translation evaluation, we use the TEP parallel data (Pilevar et al., 2011) which is a collection of 600K translated movie subtitles in colloquial Persian. Following the splits by Khashabi et al. (2020), we use a small portion of the Mizan parallel corpus (Kashefi, 2018) (collection of classic fiction) as our development (1596 sentences) and test datasets (10000 sentences).

**Tools and Baselines:** We use the Hazm library\(^3\) to normalize characters and tokenize texts. Hazm is also capable of converting colloquial text to standard text. This is done by manual rules. We use this tool as a strong baseline to compare with. We use SacreBLEU (Post, 2018) on the tokenized text for evaluation.

**Translation Model:** We use a standard sequence-to-sequence transformer-based translation model (Vaswani et al., 2017) with a six-layer BERT-based (Devlin et al., 2019) encoder-decoder architecture from HuggingFace (Wolf et al., 2019) and Pytorch (Paszke et al., 2019) with a shared SentencePiece (Kudo and Richardson, 2018) vocabulary of size 40K.\(^4\) All input and output token embeddings are summed up with the language id embedding: we use “<fa>” for standard Persian, and “<fab>” for broken Persian. First tokens of every input and output sentence are shown by the language ID. We use greedy decoding since we find greedy decoding slightly

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**Table 1:** Some of the main conversion rules for converting standard Persian to colloquial with examples. Most of these rules are inspired from Bakhshizadeh Gashti and Tabibzadeh (2019).

| Rule name | Example Standard | Colloquial |
|-----------|------------------|------------|
| “an” suffix | تهران [tehran] | تهران [tehran] |
| Verb suffix | بروم [beram] | بروم [beram] |
| Verb form | میگویم [mitgamen] | میگویم [mitgamen] |
| “ha” suffix | گولا [gola] | گولا [gola] |
| Common rules | مصحب [sahab] | مصحب [sahab] |
| Case marker | رو [ra] | رو [ra] |
| Attach pronoun | به تو [be tu] | به تو [be tu] |
| “әәست” (is) | چکارم؟ [karm ?әәست] | چکارم؟ [karm ?әәست] |
| “әәست” (is) | چکارم که [karm harmand] | چکارم که [karm harmand] |
| “әәست” (is) | چکارم [karm] | چکارم [karm] |

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\(^3\)https://github.com/sobhe/hazm

\(^4\)Code from https://github.com/rasoolims/ImageTranslate/tree/naacl21
more accurate for standardization than beam search. For machine translation, we use a similar pipeline. We pretrain the model on a tuple of three Wikipedia datasets for Persian, Arabic, and a sample of 6 million sentences from English using the MASS model (Song et al., 2019) with a shared SentencePiece (Kudo and Richardson, 2018) vocabulary of size 60K. The decoder for each language has a separate output layer in order to have language-specific output probabilities. We use a beam size of 4 for machine translation experiments.

3.2 Results

**Intrinsic evaluation:** Table 2 shows the BLEU scores of our model versus the rule-based Hazm tool. As we see in the Table, our model does a much better job in making the text closer to standard form. Figure 3 shows some examples of our conversions versus the rule-based conversion. It is worth noting that we observe some very few cases in which our model generates an irrelevant word, most likely due to the interference of the language model component in sequence-to-sequence models. Solving this issue is an interesting topic to pursue in future work.

**Extrinsic evaluation:** Table 3 shows the BLEU scores of different models trained of different types of preprocessed and post-processed data. First, we observe that standardization helps in all cases.

### Figure 1: Real examples of our random conversions of standard text to colloquial.

| Colloquial | Standard |
|------------|----------|
| و زمانی که بی‌کلامی از گویا از خودمون عفاف و سنتاپی کم | و زمانی که بی‌کلامی از گویا از خودمون عفاف و سنتاپی کم |
| دیدم که فقلید بیان حرفی نیست، باز کنیم | دیدم که فقلید بیان حرفی نیست، باز کنیم |
| نمی‌توانم یک بازگویی درمی‌آیم و کلاغ‌ها | نمی‌توانم یک بازگویی درمی‌آیم و کلاغ‌ها |
| اما ممکن است یک بازگویی درمی‌آیم و کلاغ‌ها | اما ممکن است یک بازگویی درمی‌آیم و کلاغ‌ها |

### Figure 2: Number of sentences from different genres in our evaluation development and test datasets.

| Data Style | Development | Test |
|------------|------------|------|
| Telegram groups | 43.9 | 46.4 |
| Movie subtitles | 38.8 | 40.5 |
| Persian fiction | 46.4 | 52.7 |
| Blog posts | 52.7 | 56.3 |

### Table 2: Results of standardizing our Persian colloquial evaluation data via SacreBLEU (Post, 2018).

| Data Approach | Dev. | Test |
|---------------|------|------|
| Original Data | 4.4  | 2.8  |
| Post-edit Hazm | 4.2  | 3.1  |
| Our approach  | 5.0  | 3.0  |

### Table 3: Machine translation results trained on TEP (Pilevar et al., 2011) (movie subtitles in colloquial Persian), and evaluated on the Mizan corpus (Kashefi, 2018) (standard Persian) via SacreBLEU (Post, 2018).

| Data Style | Approach | Dev. | Test |
|------------|----------|------|------|
| Original Data | No edit | 4.4  | 2.8  |
| Post-edit Hazm | Our approach | 4.9  | 3.3  |
| Preprocess Hazm | Our approach | 5.0  | 3.0  |
| Our approach  | 5.8  | 3.6  |

Second, using preprocessed data from our standardization model outperforms post-editing with standardization. One important note about the low BLEU scores is that the TEP data (Pilevar et al., 2011) consists of very short colloquial movie dialogues while the Mizan corpus (Kashefi, 2018) consists of sentences from classic fictions. This domain mismatch plus the size of the TEP data are the main causes of this low BLEU. However, our method still improves the BLEU score by a wide margin. In practice, previous work has used back-translation improve low-resource translation either in a non-iterative (Edunov et al., 2018) or iterative (Hoang et al., 2018) manner. Improvements from back-translation heavily depend on the quality of the initial model. We skip back-translation since it is not the focus of our work.

4 Conclusion

We have described an algorithm for standardizing Persian text. We show that by creating artificial training data, we can leverage commonly known patterns of breaking standard forms to colloquial, and learn an accurate standardization model. We
believe that this work is just a beginning to this line of research. Future work should investigate more sophisticated methods for standardization.

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References

Nadieh Armin and Mehrnoush Shamsfard. 2011. Converting Persian colloquium text to formal by n-grams. In Computer Society of Iran.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. CoRR, abs/1409.0473.

Yousef Bakhshizadeh Gashiri and Omid Tabibzadeh. 2019. Colloquial forms and Persian lexicons. Persian Language and Iranian Dialects, 2(6).

Mahmood Bijankhan, Javad Sheykhzadegan, Mohammad Bahrami, and Masood Ghayoomi. 2011. Lessons from building a Persian written corpus: Peykare. Language resources and evaluation, 45(2):143–164.

John Andrew Boyle. 1952. Notes on the colloquial language of Persia as recorded in certain recent writings. Bulletin of the School of Oriental and African Studies, 14(3):451–462.

Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, Doha, Qatar. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. Understanding back-translation at scale. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 489–500, Brussels, Belgium. Association for Computational Linguistics.

Weston Feely, Mehdi Manshadi, Robert E. Frederking, and Lori S. Levin. 2014. The CMU METAL Farsi NLP approach. In LREC, pages 4052–4055.

Vu Cong Duy Hoang, Philipp Koehn, Gholamreza Haffari, and Trevor Cohn. 2018. Iterative back-translation for neural machine translation. In Proceedings of the 2nd Workshop on Neural Machine Translation and Generation, pages 18–24, Melbourne, Australia. Association for Computational Linguistics.

Éva M Jeremiás. 1984. Diglossia in persian. Acta Linguistica Academiae Scientiarum Hungaricae, 34(3/4):271–287.

Omid Kashefi. 2018. Mizan: a large Persian-English parallel corpus. arXiv preprint arXiv:1801.02107.
Mohammad Taher Pilevar, Arman Cohan, Siamak Shakeri, Daniel Khashabi, Rabeeh Karimi Mahabadi, Omid Memarrast, Alireza Nourian, Mohammad Sadegh Rasooli, Sepideh Sadeghi, Erfan Sadeqi Azer, Niloofar Safi Samghabadi, Mahsa Shafaei, Saber Sheyhani, Ali Tazarv, and Yadollah Yaghoobzadeh. 2020. PARSiNLU: A suite of language understanding challenges for Persian. arXiv preprint.

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.

Behrooz Mahmoodi-Bakhtiari. 2018. Spoken vs. written Persian: Is Persian diglossic? In Alireza Korangy and Corey Miller, editors, Trends in Iranian and Persian Linguistics, chapter 10, pages 183–212. De Gruyter Mouton.

Azadeh Mirzaei and Amirsaeid Moloodi. 2016. Persian proposition bank. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 3828–3835.

Azadeh Mirzaei and Pegah Safari. 2018. Persian discourse treebank and coreference corpus. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).

Azadeh Mirzaei, Fatemeh Sedghi, and Pegah Safari. 2020. Semantic role labeling system for persian language. ACM Transactions on Asian and Low-Resource Language Information Processing (TAL-LIP), 19(3):1–12.

Alireza Nourian, Mohammad Sadegh Rasooli, Mohsen Imany, and Hesham Fuji. 2015. On the importance of Ezafe construction in Persian parsing. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 877–882.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. In Advances in neural information processing systems, pages 8026–8037.

Mohammad Taher Pilevar, Hesham Fuji, and Abdul Hamid Pilevar. 2011. TEP: Tehran English-Persian parallel corpus. In International Conference on Intelligent Text Processing and Computational Linguistics, pages 68–79. Springer.

Hanieh Poostchi, Ehsan Zare Borzeshi, and Massimo Piccardi. 2018. BiLSTM-CRF for Persian named-entity recognition. ArmanPersoNERCorpus: The first entity-annotated Persian dataset. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Mohammad Sadegh Rasooli, Manouchehr Khouhestani, and Amirsaeid Moloodi. 2013. Development of a Persian syntactic dependency treebank. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 306–314.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96, Berlin, Germany. Association for Computational Linguistics.

Mojgan Seraji. 2015. Morphosyntactic corpora and tools for Persian. Ph.D. thesis, Acta Universitatis Upsaliensis.

Mojgan Seraji, Filip Ginter, and Joakim Nivre. 2016. Universal dependencies for Persian. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 2361–2365.

Mehrnoush Shamsfard. 2011. Challenges and open problems in Persian text processing. In Proceedings of LTC.

Ali Solhju. 2019. How To Write Spoken Short Forms In Persian Dialogues. Markaz, Tehran, Iran.

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2019. MASS: Masked sequence to sequence pre-training for language generation. arXiv cs.CL 1905.02450.

Omid Tabibzadeh. 2020. Orthography of Colloquial Persian: Based on Works of Fiction and Drama Spanning a Century (1918-2018). Institute for Humanities and Cultural Studies, Tehran, Iran.

Ehsan Taher, Seyed Abbas Hoseini, and Mehrnoush Shamsfard. 2020. Beheshi-NER: Persian named entity recognition using BERT. arXiv preprint arXiv:2003.08875.

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 Advances in neural information processing systems, pages 5998–6008.
Gernot Windfuhr. 2009. *The Iranian Languages*. Psychology Press.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierec Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *ArXiv*, pages arXiv–1910.