Using Interlinear Gloses as Pivot in Low-Resource Multilingual Machine Translation

Zhong Zhou
Carnegie Mellon University
zhongzhou@cmu.edu

Lori Levin
Carnegie Mellon University
lsl@cs.cmu.edu

David R. Mortensen
Carnegie Mellon University
dmortens@cs.cmu.edu

Alex Waibel
Carnegie Mellon University
Karsruhe Institute of Technology
alex@waibel.com

Abstract

We demonstrate a new approach to Neural Machine Translation (NMT) for low-resource languages using a ubiquitous linguistic resource, Interlinear Glossed Text (IGT). IGT represents a non-English sentence as a sequence of English lemmas and morpheme labels. As such, it can serve as a pivot or interlingua for NMT. Our contribution is four-fold. Firstly, we pool IGT for 1,497 languages in ODIN (54,545 glosses) and 70,918 glosses in Arapaho and train a gloss-to-target NMT system from IGT to English, with a BLEU score of 25.94. We introduce a multilingual NMT model that tags all glossed text with gloss-source language tags and train a universal system with shared attention across 1,497 languages. Secondly, we use the IGT gloss-to-target translation as a key step in an English-Turkish MT system trained on only 865 lines from ODIN. Thirdly, we present five metrics for evaluating extremely low-resource translation when BLEU is no longer sufficient and evaluate the Turkish low-resource system using BLEU and also using accuracy of matching nouns, verbs, agreement, tense, and spurious repetition, showing large improvements.

1 Introduction

Machine polyglotism, training a universal NMT system with a shared attention through implicit parameter sharing, is very helpful low-resource settings (Firat et al.(2016)Firat, Cho, and Bengio; Zoph and Knight(2016); Dong et al.(2015)Dong, Wu, He, Yu, and Wang; Gillick et al.(2016)Gillick, Brunk, Vinyals, and Subramanya; Al-Rfou et al.(2013)Al-Rfou, Perozzi, Perozzi, and Skiena; Zhou et al.(2018)Zhou, Sperber, and Waibel; Tsvetkov et al.(2016)Tsvetkov, Sitaram, Faruqui, Lampl, Littell, Mortensen, Black, Levin, and Dyer). However, there is still a large disparity between translation quality in high-resource and low-resource settings, even when the model is well-tuned (Koehn and Knowles(2017); Sennrich and Zhang(2019); Nordhoff et al.(2013)Nordhoff, Hammarström, Forlk, and Haspelmath). Indeed, there is room for creativity in low-resource scenarios.

Morphological analysis is useful in reducing word sparsity in low-resource languages (Habash and Sadat(2006); Lee (2004); Hajič (2000)). Toward that end, we leverage a linguistic resource, Interlinear Glossed Text (IGT) (Lehmann and Croft(2015)) as shown in Table 2 (Samardzic et al.(2015)Samardzic, Schikowski, and Stoll;
| Data                                                                 | Example                                                                 |
|----------------------------------------------------------------------|-------------------------------------------------------------------------|
| Source language (German)                                            | Ich sah ihm den Film gefallen.                                          |
| Interlinear Gloss w/ target-lemma                                   | I saw he.DAT the film.ACC like.                                         |
| Target language (English)                                           | I saw him like the film.                                                |
| Source language (Hmong)                                             | Nwg yeej qhuas nwg.                                                     |
| Interlinear gloss w/ target-lemma                                   | 3SG always praise 3SG.                                                  |
| Target language (English)                                           | He always praises himself.                                              |
| Source language (Arapaho)                                           | Niine’etii3i’ teesihi’ coo’oteyou’uHohootino’ nenee3i’ neeyeiicii.     |
| Interlinear gloss w/ target-lemma                                   | live(at)-3PL on/over-ADV IC.hill(y)-0.PL.tree-NA.PL.IC.it is-3PL timber. |
| Target language (English)                                           | Trees make the woods.                                                   |

Table 1: Examples of interlinear glosses in different source languages.

Moeller and Hulden(2018)). We propose to use interlinear gloss as a pivot to address the harder problem of morphological complexity and source of data sparsity in multilingual NMT. We combine the benefits of both multilingual NMT and linguistic information through the use of interlinear glosses as a pivot representation. Our contribution is four-fold.

1. We present our multilingual model using a single attention in translating from interlinear glosses into a target language. Our best multilingual NMT result achieves a BLEU score of 25.94, +5.65 above a single-source single-target NMT baseline.

2. We present two linguistic datasets that we normalized, cleaned and filtered: the cleaned ODIN dataset includes 54,545 lines of IGT in 1,496 languages (Lewis and Xia(2010); Xia et al.(2014)Xia, Lewis, Goodman, Crowgey, and Bender), and the cleaned Arapaho dataset includes 70,918 lines of IGT (Cowell and O’Gorman(2012); Wagner et al.(2016)Wagner, Cowell, and Hwang).

3. We present a three-step approach for extremely low-resource translation. We demonstrate it by training on only 865 lines of data.

   (a) We use a morphological analyzer to automatically generate interlinear glosses with source lemma.

   (b) We translate the source lemma into target lemma in through alignments trained from parallel data.

   (c) We translate from interlinear glosses with target lemma to target language by using the gloss-to-target multilingual NMT developed in 1 presented above.

4. We present five metrics for evaluating extremely low-resource translation when BLEU no longer suffices. Our system using interlinear glosses achieves an improvement of +44.44% in Noun-Verb Agreements, raising fluency.

We present our cleaned data followed by gloss-to-target models and our three-step Turkish-English NMT in Section 3 and 4. We evaluate in Section 5.

2 Related Works

2.1 Multilingual Neural Machine Translation

Multilingual NMT’s objective is to translate from any of $N$ input languages to any of $M$ output languages (Firat et al.(2016)Firat, Cho, and Bengio; Zoph and Knight(2016); Dong et al.(2015)Dong, Wu, He, Yu, and Wang; Gillick et al.(2016)Gillick, Brunk, Vinyals, and Subramanya; Al-Rfou et al.(2013)Al-Rfou, Perozzi, and Skiena; Tsvetkov et al.(2016)Tsvetkov, Sitaram, Faruqui, Lample, Littell, Mortensen, Black, Levin, and Dyer). Many multilingual NMT systems work on a universal model with a shared attention mechanism with Byte-Pair Encoding (BPE) (Johnson et al.(2017)Johnson, Schuster, Le, Krikun, Wu, Chen, Thorat, Viégas, Wattenberg, Corrado et al.; Ha et al.(2016)Ha, Niehues, and Waibel; Zhou et al.(2018)Zhou, Sperber, and Waibel). Its simplicity and implicit parameter sharing helps with low-resource translation and zero-shot translation (Johnson et al.(2017)Johnson, Schuster, Le, Krikun, Wu, Chen, Thorat, Viégas, Wattenberg, Corrado et al.; Firat et al.(2016)Firat, Cho, and Bengio).

2.2 Morpheme-Level Machine Translation

To build robustness (Chaudhary et al.(2018)Chaudhary, Zhou, Levin, Neu-
Table 2: Examples of the translation sequence using interlinear glosses.

| Data | Example |
|------|---------|
| 1. Source language (Turkish) | Kadin dans ediyor. |
| 2. Interlinear gloss with source-lemma | Kadin.NOM dance ediyor-AOR.3.SG. |
| 3. Interlinear gloss with target-lemma | Woman.NOM dance do-AOR.3.SG. |
| 4. Target language (English) | The woman dances. |

| 1. Source language (Turkish) | Adam kadin-i gör-dü. |
| 2. Interlinear gloss with source-lemma | Adam.NOM kadin-ACC gör-AOR.3.SG. |
| 3. Interlinear gloss with target-lemma | Man.NOM woman-ACC see-PST.3.SG. |
| 4. Target language (English) | The man saw the woman. |

Table 3: Notation used in the translation sequence.

| Notation | Meaning in translation sequence |
|----------|---------------------------------|
| 1 | Source language (Turkish) text |
| 2 | Interlinear gloss with source-lemma |
| 3 | Interlinear gloss with target-lemma |
| 4 | Target language (English) text |

2.3 Factored Machine Translation

Factored models translate a composition of annotations including word, lemma, part-of-speech, morphology, and word class into the target language (Koehn and Hoang(2007); Yeńiterzi and Oflazer(2010)). In the era of NMT, morphological information and grammatical decomposition that are produced by a morphological analyzer are employed (García-Martínez et al.(2016); García-Martínez, Barrault, and Bougares; B Burlot et al.(2017); Burlot, García-Martínez, Barrault, Bougares, and Yvon(2017)).

2.4 Interlinear Gloss Generation

Interlinear gloss is a linguistic representation of morphosyntactic categories and cross-linguistic lexical relations (Samardzic et al.(2015); Samardzic, Schikowski, and Stoll; Moeller and Hulden(2018)). IGT is used in linguistic publications and field notes to communicate technical facts about languages that the reader might not speak, or to convey a particular linguistic analysis to the reader. Typically, there are three lines to an IGT. The first line consists of text segments in an object language, which we call the source language in this paper. The third line is a fluent translation in the metalanguage, which we call the target language. In our work, the target language (metalanguage) is always English. The source (object) languages are the 1,496 languages of the ODIN (Lewis and Xia(2010); Xia et al.(2014)) database plus Arapaho, for which a large collection of field notes has been published (Cowell and O’Gorman(2012)). In the middle (interlinear) line of an IGT, each object language word allows words to share embedding while allowing variation in meanings (Cotterell and Schütze(2015); Chaudhary et al.(2018); Chaudhary, Zhou, Levin, Neubig, Mortensen, and Carbonell; Renduchintala et al.(2019); Renduchintala, Shapiro, Duh, and Koehn; Passban et al.(2018); Passban, Liu, and Way; Dalvi et al.(2017); Dalvi, Durrani, Sajjad, Belinkov, and Vogel), shrinks the vocabulary size introduces smoothing (Goldwater and McClosky(2005)), and makes fine-grained correction (Stroppa et al.(2006); Stroppa, Groves, Way, and Sarasola; Matthews et al.(2018); Matthews, Neubig, and Dyer).
| Normalized Gloss | Meaning of the Abbreviations | Glosses in the Turkish Odin Data |
|------------------|-----------------------------|---------------------------------|
| NMLZ             | Nominalizer                 | NML, NOMZ, FNom, NOML            |
| PRS              | Present tense               | PRES, PR, pres, Pres, PRESENT    |
| PST              | Past tense                  | PA, Pst, PST, Past, pst, PAST, PT, PTS, REP-PAST, PST1S, past |
| ABL              | Ablative                    | Abl, Abli, abl, ABL              |
| ADV              | Adverb(ial)                 | ADVL, Adv                       |
| RPRT             | Reported Past tense         | ReportedPast, REPPAST            |

Table 4: Examples of the normalization mapping created for the Turkish ODIN data.

| Tags            | Meaning of the Abbreviations | Sets of Normalized Glosses Included |
|-----------------|------------------------------|------------------------------------|
| P1pl            | 1st person plural possessive | 1, PL, POSS                        |
| A1sg            | 1st person singular          | 1, SG                              |
| Reflex          | Reflexive Pronoun            | REFL                               |
| NarrPart        | Evidential participle        | EVID, PTCP                         |
| AorPart         | Aorist participle            | AOR, PTCP                          |
| PresPart        | Present participle           |PRS, PTCP                          |

Table 5: Examples of the normalization mapping created for the outputs from the Turkish morphological analyzer.

“hoot nii3eihit” means “a tree is nice”. The interlinear gloss with source-language lemmas is “hohoot nii3eihit-3.S” and the interlinear gloss with target-language lemmas is “Tree good-3.S”.

A benefit of IGT is that there is a one-to-one mapping between each segment of the source sentence to the gloss (Samardzic et al.(2015)Samardzic, Schikowski, and Stoll). Researchers have tried to generate interlinear glosses automatically by using supervised POS tagging, word disambiguation and a dictionary (Samardzic et al.(2015)Samardzic, Schikowski, and Stoll), and using conditional random fields and active learning (Moeller and Hulden(2018)).

3 Data

3.1 Newly Cleaned Datasets

We present two linguistic datasets that we have cleaned and partially normalized: the partially normalized ODIN dataset that includes 54,545 lines of IGT in 1,496 languages (Lewis and Xia(2010); Xia et al.(2014)Xia, Lewis, Goodman, Crowgey, and Bender), and the cleaned Arapaho dataset that includes 70,918 lines of IGT (Cowell and O’Gorman(2012); Wagner et al.(2016)Wagner, Cowell, and Hwang).

ODIN is a unique multilingual database of IGT that was scraped from the Web. The IGTs in ODIN come from many different publications with different standards for morpheme labels. A consequence of the diversity is that morpheme labels in ODIN are not standardized. For example, “singular” may be “S”, "SG", or "SING", and when combined with “3” for third person, there may or may not be a delimiter, resulting such diverse labels as "3S", "3.s", "3SG", and "3.sing".

In order to reduce the sparsity and diversity of morpheme labels, we normalized them according to the Leizig conventions (Lehmann(1982); Croft(2002)) (preferred), and the Unimorph conventions (Sylak-Glassman(2016); Kirov et al.(2016)Kirov, Sylak-Glassman, Que, and Yarowsky; Sylak-Glassman et al.(2015)Sylak-Glassman, Kirov, Yarowsky, and Que) for labels not covered by the Leizig conventions. For the work presented here, we normalized only those morpheme labels that were found in ODIN’s 1,081 lines of Turkish IGT. However, we normalized those morpheme labels throughout the entire ODIN database. We show a few normalized examples in Table 6.

The Arapaho dataset was originally created in ToolBox (Buseman(2020)). Cleaning of this dataset consisted of running an in-house script that found lingering formatting errors. Some of the errors were corrected by Andy Cowell, and others remain in a default format created by our script and will be corrected in the future.
Table 6: Examples of the normalization of glosses from the Turkish ODIN data.

| Analyzer Outputs          | Example                                      |
|---------------------------|----------------------------------------------|
| Before normalization      | Ahmet self-3.sg-ACC very admire-Progr.-Rep.Past. |
| After normalization       | Ahmet self-3.SG-ACC very admire-PROG-Rep.PST.  |
| Before normalization      | Woman.NOM dance do-AOR.3SG.                  |
| After normalization       | Woman.NOM dance do-AOR.SG.3.                 |
| Before normalization      | Man.NOM woman-ACC see-PAST.3SG.              |
| After normalization       | Man.NOM woman-ACC see-PST.SG.3.              |

Table 7: Examples of the normalization process for the output of the Turkish morphological analyzer.

| Analyzer Outputs          | Example                                      |
|---------------------------|----------------------------------------------|
| Before normalization      | Kadi+A3sg+Pnon+Nom dans+A3sg+Pnon+Nom et+Prog1+A3sg. |
| After normalization       | Kadin.3.SG.NPOSS.NOM dans.3.SG.NPOSS.NOM ediyor-PROG.3.SG. |
| Before normalization      | Adam+A3pl+Pnon+Nom kadi+A3sg+Pnon+Acc gör+Past+A3sg. |
| After normalization       | Adam.3.SG.NPOSS.NOM kadi.3.SG.NPOSS.ACC gör-PST.3.SG. |
| Before normalization      | Ali+A3sg+Pnon+Nom hakkinda+A3sg+P3sg+Loc met+Prop+A3sg+Pnon+Nom ne düünüyor+A3sg+Pnon+Nom? |
| After normalization       | Ali.3.SG.NPOSS.NOM hakkinda.3.SG.POSS.LOC met.3.SG.NPOSS.NOM ne düünüyor.3.SG.NPOSS.NOM? |

3.2 Data Preparation: Turkish-English NMT

The 1,081 Turkish-English glosses are split into training, validation, and test sets with the ratio of 0.8,0.1,0.1. Our training data only contains 865 lines. We choose Turkish because it is morphologically rich (Matthews et al.(2018)Matthews, Neubig, and Dyer; Botha and Blunsom(2014)), agglutinative, and has words that cannot be translated as a single word in other languages (Clifton and Sarkar(2011); El-Kahlout and Oflazer(2006); Bisazza and Federico(2009)).

4 Models

For convenience, we use 1, 2, 3, 4 to denote each line of the translation sequence as shown in Table 3.

4.1 An Extension to Multilingual NMT: Gloss-to-Target Translation

In Figure 1, we show a simple setup for multilingual translation on the top. Each source sentence is tagged with the source and language tags and is added to the training data. In Figure 2, we also show our model of gloss-to-target translation, which introduces a new extension to multilingual NMT.

In our gloss-to-target translation, we train a multilingual NMT system on 57,608 lines across 1,497 languages. Our source sentences are the interlinear glosses with target-lemma (3), and our target sentences are the target translations (4). We tag each glossed text with the gloss-source language tag, for example, we tag Hmong glosses with “blu”. As such, our training data on the source side contains “blu 1SG be_thirsty water” (Hmong), “cmn 1SG be_thirsty” (Chinese) and “deu 1SG.ACC be_thirsty” (German), and our training data on the target side is “I am thirsty” in English. We proceed to train using a unified attention mechanism. Even though the gloss only contains the target-lemma, our system is informed of the source language.

In our multilingual NMT translation, we use a minibatch size of 64, a dropout rate of 0.3, 4 RNN layers of size 1000, a word vector size of 600, number of epochs of 13, a learning rate of 0.8 that decays at the rate of 0.7 if the validation score is not improving or it is past epoch 9. Our code is built on OpenNMT (Klein et al.(2017)Klein, Kim, Deng, Senellart, and Rush) and we evaluate our models using BLEU scores (Papineni et al.(2002)Papineni, Roukos, Ward, and Zhu), and qualitative evaluation.

We train a baseline attentional NMT model without adding the source language tags, as well as other system variation, some of which include Arapaho and ODIN in Section 5.
Table 8: Examples of interlinear gloss generation (1→2→3) from the output from the Turkish morphological analyzer. Notation of the translation sequence follows from Table 3.

| Analyzer Outputs | Example | Reference in ODIN |
|------------------|---------|------------------|
| Before normalization | Kadi+A3sg+Pnon+Nom dans+A3sg+Pnon+Nom et+Prog1+A3sg. | Woman.NOM dance do-AOR.3.SG. |
| After normalization | Kadin.3.SG.NPOSS.NOM dans.3.SG.NPOSS.NOM ediyor-PROG.3.SG. | Man.NOM woman-ACC see-PST.3.SG. |
| After using a dictionary | Woman.3.SG.NPOSS.NOM dance.3.SG.NPOSS.NOM be-PROG.3.SG. | Man.3.SG.NPOSS.NOM woman.3.SG.NPOSS.ACC see-PST.3.SG. |

Table 9: Examples of Gloss-to-Target (3→4 in Table 3) NMT translation results. The source is the interlinear gloss with target(English)-lemma and the target is the fluent English. Notation of the translation sequence follows from Table 3. Note that the ODIN dataset is not clean, and the second example above is a case where two words are concatenated together without space followed by a unnecessary punctuation symbol. This example serves to show that our NMT output automatically corrects typos in producing fluent target(English) sentence.

| Interlinear Gloss w/ Target-lemma | NMT Result in Target Language | Reference Target Sentence |
|----------------------------------|-------------------------------|---------------------------|
| Peter and Mary that/those not came-3SG/3PL | Peter and Mary, he didn’t come. | Peter and Mary, they didn’t come. |
| PERF.AV-buy NOM-man ERG-fish DAT-store | The man bought fish at the store. | The man bought fish at the-store’. |
| AGR-do-make-ASP that waterpot AGR-fall-ASP | The girl made that waterpot fall. | The girl made the waterpot fall. |

4.2 Case Study: Turkish-English Translation

We use our gloss-to-target model above as the third step in our Turkish-English Translation pipeline. We present a case study of Turkish-English translation using 865 lines of training data.

4.2.1 1→2: Generation of Interlinear Gloss with Source-Lemma

We use a morphological analyzer (Oflazer(1994)) to generate morphological tags and a root for each word token in the source text. After normalizing the morpheme labels, we produce an interlinear gloss with source-lemma. In Table 8, we show the interlinear gloss with source-lemma in every second line.

4.2.2 2→3: Generation of Interlinear Gloss with Target-Lemma

We use a dictionary produced by aligning parallel corpora to construct interlinear gloss with target English tokens from source Turkish tokens (Dyer et al.(2013)Dyer, Chahuneau, and Smith). In order to produce a higher quality dictionary, instead of choosing the 865 lines training data to construct alignments, we use an additional parallel corpus with 57,608 lines. This data, which is only used to create a dictionary, would be unnecessary if a high-quality dictionary already existed. Using the dictionary, we generate interlinear glosses with target English tokens as shown by every third line in Table 8.

4.2.3 3→4: Training NMT system for Gloss-to-Target Translation

We use our multilingual gloss-to-target NMT model trained above to translate from glosses with target-lemma (3) into the target language (4).

5 Results

5.1 Multilingual Gloss-to-Target NMT

In the description of our results, we will use a number of labels. In Table 10, we use Turkish to denote the baseline translation system (taking all the interlinear glosses with target lemma (3) in our 865 lines of Turkish data and their target translations (4) and training a single-source single-target translation system). We use ODIN to denote the baseline
translation system in which we take all the interlinear glosses with target lemma (3) in ODIN and their target translations (4) and train a single-source single-target translation system. We also use Arapaho to denote the baseline translation system of taking all the interlinear glosses with target lemma (3) in Arapaho and their target translations (4) and train a single-source single-target translation system. We use ODIN+Arapaho to denote the single-source single-target NMT model trained on both the ODIN and Arapaho datasets. We use ODIN_multi to denote the multilingual NMT model trained for gloss-to-target translation by tagging each gloss with its source language labels, for example “blu” for Hmong. We use ODIN+Arapaho_multi to denote the multilingual NMT model produced by tagging each gloss with its source language labels combining both the ODIN and Arapaho datasets.

We see that ODIN_multi raises the BLEU score to 23.05, an increase of +2.76 compared to the baseline ODIN as shown in Table 10 and Table 9. After adding the Arapaho data to ODIN, our ODIN+Arapaho raises the BLEU score to 25.94, an increase of +5.65 over that of ODIN. After adding the Arapaho data to ODIN_multi, our ODIN+Arapaho_multi has a BLEU score of 25.85, a increase of +2.80 over that of ODIN_multi. However, the BLEU score of ODIN+Arapaho_multi is lower than that of ODIN+Arapaho by -0.09, although it is a small difference. We think a contributing factor to the similar performance of ODIN+Arapaho and ODIN+Arapaho_multi is because the Arapaho dataset, though it is relatively large, is monolingual. Even though we train in a multilingual fashion in ODIN+Arapaho_multi, most of the training data is skewed towards the monolingual Arapaho data, therefore its performance is similar to that of ODIN+Arapaho.

5.2 Case Study: Turkish-English NMT

We use a few labels in the descriptions of our experiments. In Table 11 and Table 12, Baseline1 denotes an attentional NMT system that trains on the 865 lines of Turkish-English parallel data without using any information from the the interlinear gloss; Baseline2 denotes attentional NMT system that trains on an additional 57,608 lines of Turkish-English parallel data; Generation denotes the interlinear gloss with target-lemma generation step (1→2→3→4).

We use IGT_src to denote our translation through gloss with source-lemma as a pivot into target language (1→2→4). We use IGT_tgt to denote our translation through gloss with target-lemma as a
pivot into target language \((1\to 2\to 3\to 4)\).

For evaluation, the BLEU score does not suffice for evaluating our translation using only 865 lines of data, especially when our translating goal is to improve meaningful translation and improve fine-grained translation performance.

We present five metrics that we have designed for our evaluating purpose on top of both 4-gram and 1-gram BLEU scores. They are: noun-match accuracy, verb-match accuracy, subject-object agreement accuracy, and tense-match accuracy. The noun-match accuracy is the percentage correctly predicted string-matched nouns; and the verb-match accuracy is the percentage correctly predicted string-matched verbs. The subject-verb agreement accuracy is the percentage of correctly predicted source lemmas are tagged with subject-verb agreement information, the model finds it hard to learn about the target lemmas. \(IGT\_tgt\) addresses this issue. The metric of non-repetition performs very well, beating all baselines. Our model \(IGT\_src\) beats \textit{baseline1} and \textit{baseline2} in all metrics excluding subject-verb agreement.

The model \textit{baseline2} performs better than \textit{baseline1} on verb-match accuracy, subject-verb agreement accuracy, and tense-match accuracy, but is worse off in BLEU scores as well as the metric of matching nouns. This is interesting because we expect that our performance will increase with increased amount of data. However, it is worth noting that linguistic gloss data is very domain specific. The Turkish ODIN dataset has a relatively narrow domain which may not be covered by the parallel data that is injected. Therefore, adding more data may not help with the translation.

Table 12: Qualitative Evaluation. All experiments except the starred \textit{Baseline2} use 865 lines of training data. \textit{Baseline2} uses additional 57608 lines of parallel data. Notation of the translation sequence follows from Table 3.

| Source Sentence Sequence | Gold | Baseline1 | Baseline2 | IGT\_src | Generation | IGT\_tgt |
|--------------------------|------|-----------|-----------|-----------|------------|----------|
| Problemi çöz-mek zor-dur. | To solve the problem is difficult. | Ali read the book. | As for this book, it is known that it is known as a result. | As for the book, the book. | Solv-3.SG.ACC the is difficult-3.SG.COP.PRS. | The fact that it is difficult for that. |
| Fatma bu kitabkimin yazdı mı sanyor. | Who does Fatma think wrote this book. | As for Fatma knows that I one. | As for Fatma, Fatma knows that I left. | Fatma-3.SG.NOM this-DET kitabkimin ATATURK-3.SG.NOM wrote-3.SG.NOM it-3.SG.NOM. | As for Fatma, it is possible that he wrote this. |
| Adam cocuga top verdi. | The man gave the child a ball. | As for the book, the book, the book. | Ahmet read the book. | the girl that the book. | Man-1.3.SG.NOM.POSS child-3.SG.DAT ball-3.SG.NOM. | The man's child is the ball. |

The model \textit{baseline2} performs better than \textit{baseline1} on verb-match accuracy, subject-verb agreement accuracy, and tense-match accuracy, but is worse off in BLEU scores as well as the metric of matching nouns. This is interesting because we expect that our performance will increase with increased amount of data. However, it is worth noting that linguistic gloss data is very domain specific. The Turkish ODIN dataset has a relatively narrow domain which may not be covered by the parallel data that is injected. Therefore, adding more data may not help with the translation.

Our model \(IGT\_src\) beats \textit{baseline1} and \textit{baseline2} in all metrics excluding subject-verb agreement. The reason that the subject-verb agreement does not perform well in \(IGT\_src\) is because \(IGT\_src\) is a factored model created by combining source text with morphological tags. Though source lemmas are tagged with subject-verb agreement information, the model finds it hard to learn about the target lemmas. \(IGT\_tgt\) addresses this issue. The metric of non-repetition performs very well, beating all baselines. Our model \(IGT\_tgt\) raises the metric of matching nouns by +20.15, raises the metric of matching verbs by +15.74, increases the metric of noun-verb agreements by +44.44, raises the metric of matching tense by +26.85, raises the 1-gram BLEU by +0.20, and raises the 4-gram BLEU by +1.66 comparing with \textit{baseline1}. It also beats \textit{baseline2} in all metrics. The reason that the noun-verb agreement performs very well in \(IGT\_tgt\) is that the model is actively learning
information of the target lemma. For example, if “he-3.SG walks-3.SG” is present in training, then the model learns the noun-verb agreement in the space of target lemma very well. The metric of non-repetition performs very well showing significant improvement over all baselines.

Our five metrics only evaluate individual sentences, but there are corpus-level patterns that are also worthy of comment. For example, in baseline2, “the book” is repeated across all translations even when the source sentence is totally unrelated.

In extreme low-resource scenarios like ours, qualitative evaluation is more important than quantitative evaluation. In Table 12, we see clearly that the two baseline NMT systems are hallucinating. The baseline translations have nothing in common with the source sentence, except fluency. The model IGT_tgt also hallucinates as it is exposed to very little information regarding the target lemmas during training. However, our model IGT_tgt produce meaningful translations that preserves the content of the source sentence to a certain extent while also achieving fluency through a good gloss-to-target NMT system.

6 Conclusion
We present the cleaned and normalized Arapaho and the ODIN datasets and our multilingual model in translating from interlinear glosses to fluent target language. In addition, we present a three-step solution to extremely low-resource translation training on 865 lines of data with linguistic information as a case study. Finally, we present five metrics for evaluating extremely low-resource translation and show that our NMT system performs well in noun-verb agreements.

We would benefit from a more detailed gloss normalization process. We also would like to explore disambiguation in a morphological analyzer (Shen et al.(2016))Shen, Clothiaux, Tagtow, Littell, and Dyer) and more detailed morpheme segmentation. Furthermore, IGT is ubiquitous in linguistics publications and lecture notes. Future work could increase the size of ODIN by including IGTs from newly available publications.

References
Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2013. Polyglot: Distributed word representations for multilingual nlp. In Proceedings of the 17th Conference on Computational Natural Language Learning, pages 183–192, Sofia, Bulgaria. Association for Computational Linguistics.

Arianna Bisazza and Marcello Federico. 2009. Morphological pre-processing for turkish to english statistical machine translation. In IWSLT, pages 129–135.

Jan Botha and Phil Blunsom. 2014. Compositional morphology for word representations and language modelling. In International Conference on Machine Learning, pages 1899–1907.

Franck Burlot, Mercedes Garcia-Martinez, Loïc Barrault, Fethi Bougares, and François Yvon. 2017. Word representations in factored neural machine translation. In Conference on Machine Translation, volume 1, pages 43–55.

Alan Buseman. 2020. Field Linguists’ ToolKit. https://software.sil.org/toolbox/. [Online; accessed 13-Feb-2020].

Aditi Chaudhary, Chunting Zhou, Lori Levin, Graham Neubig, David R Mortensen, and Jaime G Carbonell. 2018. Adapting word embeddings to new languages with morphological and phonological subword representations. arXiv preprint arXiv:1808.09500.

Junyoung Chung, Kyunghyun Cho, and Yoshua Bengio. 2016. A character-level decoder without explicit segmentation for neural machine translation. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, pages 1693–1703.

Ann Clifton and Anoop Sarkar. 2011. Combining morpheme-based machine translation with post-processing morpheme prediction. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 32–42. Association for Computational Linguistics.

Ryan Cotterell and Hinrich Schütze. 2015. Morphological word-embeddings. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1287–1292.

Andrew Cowell and Timothy O’Gorman. 2012. Speech-genre effects on statistical measurements of arapaho language competency. Algonquian Papers-Archive, 44:22–36.

William Croft. 2002. Typology and universals. Cambridge University Press.

Fahim Dalvi, Nadir Durrani, Hassan Sajjad, Yonatan Belinkov, and Stephan Vogel. 2017. Understanding and improving morphological learning in the neural machine translation decoder. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 142–151.
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, pages 1723–1732.

Chris Dyer, Victor Chahuneau, and Noah A Smith. 2013. A simple, fast, and effective reparameterization of ibm model 2. In Proceedings of the 12th Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technologies, pages 644–648.

Ilknur Durgar El-Kahlout and Kemal Oflazer. 2006. Initial explorations in english to turkish statistical machine translation. In Proceedings of the Workshop on Statistical Machine Translation, pages 7–14. Association for Computational Linguistics.

Orhan Firat, Kyunghyun Cho, and Yoshua Bengio. 2016a. Multi-way, multilingual neural machine translation with a shared attention mechanism. In Proceedings of the 15th Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technologies, pages 866–875.

Mercedes García-Martínez, Loïc Barrault, and Fethi Bougares. 2016. Factored neural machine translation. arXiv preprint arXiv:1609.04621.

Dan Gillick, Cliff Brunk, Oriol Vinyals, and Amarnag Subramanya. 2016. Multilingual language processing from bytes. In Proceedings of the 15th Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technologies, pages 1296–1306.

Sharon Goldwater and David McClosky. 2005. Improving statistical mt through morphological analysis. In Proceedings of the conference on human language technology and empirical methods in natural language processing, pages 676–683. Association for Computational Linguistics.

Thanh-Le Ha, Jan Niehues, and Alexander Waibel. 2016. Toward multilingual neural machine translation with universal encoder and decoder. arXiv preprint arXiv:1611.04798.

Nizar Habash and Fatiha Sadat. 2006. Arabic preprocessing schemes for statistical machine translation. In Proceedings of the Human Language Technology Conference of the NAACL, Companion Volume: Short Papers, pages 49–52. Association for Computational Linguistics.

Jan Hajíč. 2000. Machine translation of very close languages. In Sixth Applied Natural Language Processing Conference.

Chris Hokamp. 2017. Ensembling factored neural machine translation models for automatic post-editing and quality estimation. arXiv preprint arXiv:1706.05083.

Melvin Johnson, Mike Schuster, Quoc V Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, et al. 2017. Google’s multilingual neural machine translation system: Enabling zero-shot translation. Transactions of the Association for Computational Linguistics, 5:339–351.

Christo Kirov, John Sylak-Glassman, Roger Que, and David Yarowsky. 2016b. Very-large scale parsing and normalization of Wiktionary morphological paradigms. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 3121–3126.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. Opennmt: Opensource toolkit for neural machine translation. Proceedings of the 55th annual meeting of the Association for Computational Linguistics, System Demonstrations, pages 67–72.

Philipp Koehn and Hieu Hoang. 2007. Factored translation models. In Proceedings of the 2007 joint conference on empirical methods in natural language processing and computational natural language learning (EMNLP-CoNLL).

Philipp Koehn and Rebecca Knowles. 2017. Six challenges for neural machine translation. arXiv preprint arXiv:1706.03872.

Young-Suk Lee. 2004. Morphological analysis for statistical machine translation. In Proceedings of HLT-NAACL 2004: Short Papers, pages 57–60. Association for Computational Linguistics.

Christian Lehmann. 1982. Directions for interlinear morphemic translations. Folia linguistica, 16(1-4):199–224.

Christian Lehmann and William Croft. 2015. Leipzig glossing convention. https://www.eva.mpg.de/lingua/resources/glossing-rules.php. [Online; accessed 19-Jan-2019].

William D Lewis and Fei Xia. 2010. Developing odin: A multilingual repository of annotated language data for hundreds of the world’s languages. Literary and Linguistic Computing, 25(3):303–319.

Wang Ling, Isabel Trancoso, Chris Dyer, and Alan W Black. 2015. Character-based neural machine translation. arXiv preprint arXiv:1511.04586.

Austin Matthews, Graham Neubig, and Chris Dyer. 2018. Using morphological knowledge in open-vocabulary neural language models. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1435–1445.
Sarah Moeller and Mans Hulden. 2018. Automatic glossing in a low-resource setting for language documentation. In Proceedings of the Workshop on Computational Modeling of Polysynthetic Languages, pages 84–93.

Sebastian Nordhoff, Harald Hammarström, Robert Forkel, and Martin Haspelmath. 2013. Glottolog 2.0.

Kemal Oflazer. 1994. Two-level description of turkish morphology. Literary and linguistic computing, 9(2):137–148.

Kishore Papineni, Salim Roukos, Todd Ward, and Weijing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting on association for computational linguistics, pages 311–318. Association for Computational Linguistics.

Peyman Passban, Qun Liu, and Andy Way. 2018. Improving character-based decoding using target-side morphological information for neural machine translation. arXiv preprint arXiv:1804.06506.

Adithya Renduchintala, Pamela Shapiro, Kevin Duh, and Philipp Koehn. 2019. Character-aware decoder for translation into morphologically rich languages. In Proceedings of Machine Translation Summit XVII Volume 1: Research Track, pages 244–255.

Tanja Samardzic, Robert Schikowski, and Sabine Stoll. 2015. Automatic interlinear glossing as two-level sequence classification. In Proceedings of the 9th SIGHUM Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities (LaTeCH), pages 68–72.

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, pages 1715–1725.

John Sylak-Glassman, Christo Kirov, David Yarowsky, and Roger Que. 2015. A language-independent feature schema for inflectional morphology. 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 674–680.

Jörg Tiedemann. 2012. Character-based pivot translation for under-resourced languages and domains. In Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics, pages 141–151. Association for Computational Linguistics.

Sarah Moeller and Mans Hulden. 2018. Automatic glossing in a low-resource setting for language documentation. In Proceedings of the Workshop on Computational Modeling of Polysynthetic Languages, pages 84–93.

John Sylak-Glassman. 2016. Unimorph. http://unimorph.org/. [Online; accessed 19-Jan-2019].

John Sylak-Glassman, Christo Kirov, David Yarowsky, and Roger Que. 2015. A language-independent feature schema for inflectional morphology. 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 674–680.