Translating the Unseen? Yorùbá→English MT in Low-Resource, Morphologically-Unmarked Settings

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Abstract
Translating between languages where certain features are marked morphologically in one but absent or marked contextually in the other is an important test case for machine translation. When translating into English which marks (in)definiteness morphologically, from Yorùbá which uses bare nouns but marks these features contextually, ambiguities arise. In this work, we perform fine-grained analysis on how an SMT system compares with two NMT systems (BiLSTM and Transformer) when translating bare nouns in Yorùbá into English. We investigate how the systems what extent they identify BNs, correctly translate them, and compare with human translation patterns. We also analyze the type of errors each model makes and provide a linguistic description of these errors. We glean insights for evaluating model performance in low-resource settings. In translating bare nouns, our results show the transformer model outperforms the SMT and BiLSTM models for 4 categories, the BiLSTM outperforms the SMT model for 3 categories while the SMT outperforms the NMT models for 1 category.

Keywords: Machine Translation, ResourceScarce language, Yorùbá, LSTM, Transformer, bare nouns.

1 Introduction
Languages differ with regard to how grammatical information such as “case” and “number” are expressed. In some languages, this information is overtly marked using morphological or syntactic means, whereas in others it has to be inferred from context. This asymmetry of information representation poses an important problem for machine translation (Mitkov, 1999; Hardmeier, 2012). Several phenomena where asymmetry arises have been identified as challenging problems for machine translation. These include: pronoun translation and coreference (Guillou et al., 2019), politeness (Sennrich et al., 2016), lexical cohesion (Carpuat, 2009), and lexical disambiguation (Gonzales et al., 2017).

Asymmetry of information representation presents an interesting test case for MT systems because it can shed light on their true linguistic ability (Voita et al., 2018; Bawden et al., 2017). It is, therefore, important to use evaluation measures which can capture this aspect of the translation task. However, the most popular evaluation metric for machine translation, the BLEU score (Papineni et al., 2002a), is a coarse metric which can often hide these fine-grained morphological and semantic distinctions. In fact, a high BLEU score is no guarantee of improved translation quality and BLEU, being based on precision on short ngrams, may be poorly suited for measuring the coherence and grammaticality of a sentence.

In this paper we investigate the performance of Yorùbá¹ to English Machine Translation. We specifically evaluate performance on translating Bare nouns (BNs). BNs (Cheng and Sybesma, 1999; Krifka, 2003; Chierchia, 1998; Larson, 1985; Carlson, 1989) are nouns without an overt determiner or quantifier. For instance "houses" in Houses are expensive in New York is a BN. Whereas English accounts for only plural BNs, BNs in Yorùbá are number neutral and can also be definite or indefinite depending on the context. Consider the following example:

(1) Bàbá ra iswa
FATHER BUY YAM

¹Yorùbá is a tone language that belongs to the Yoruboid group of the Kwa branch of the Niger-Congo language family, which is spoken by over 40 million in Nigeria. Yorùbá is spoken primarily in western Nigeria and eastern Benin, with communities in Sierra Leone and Liberia, and expatriate communities throughout Africa, Europe, and the Americas.
In Example (1), the BN *isu yam* can be translated into English in four ways as: the indefinite singular *a yam*, an indefinite plural *some yams*, a definite singular *the yam*, and a definite plural *the yams*. This poses a challenge akin to anaphora resolution, as the correct translation of Yorùbá BNs can only be determined by examining the context in which the BN occurs in the source text. The context can span one or more preceding or current words, phrases, clauses or sentences. It can also include world knowledge.

Our study provides a fine grained analysis that sheds light on issues in MT that are not often discussed in mainstream research. We turn away from the current research trend in massively multilingual translation systems, to this largely underexplored fine-grained aspect of the MT problem. We investigate how SMT and NMT systems compare in general, but also specifically w.r.t. translation of BNs.

Although NMT has recently been reported to outperform SMT even in low-resource settings, these findings were reported for systems translating between somewhat similar languages (e.g., languages that belong to the same language family, have overlapping vocabulary and similar script) (Junczys-Dowmunt et al., 2016; Conneau et al., 2017; Lample et al., 2017; Wang et al., 2019) such as English → French, German → French, German → Italian; languages for which large corpora exists. In this work, we collect a new dataset and use it to test whether the same NMT advantage persists by exploring two typologically dissimilar languages belonging to different language families: Yorùbá and English. This work bears significance not only to Yorùbá but to analytic languages, low-resource languages, and languages that have BNs.

Our contributions are as follows: (1) We align a new dataset for the Yorùbá and English low-resource setting. (2) We use our dataset to develop statistical and NMT Yorùbá → English models. (3) We study the linguistic ability of our models in disambiguating BNs.

The rest of the paper is organized as follows: Section 2 is a description of disambiguation patterns of Yorùbá BNs. We discuss related work in Section 3. Section 4 presents the datasets, data collection process, and preprocessing. In Section 5, we present our methods. We present results of our models and an evaluation of BN disambiguation in Section 6. We conclude in Section 7.

## 2 Disambiguating Yorùbá BNs

A number of contextual variables are important when disambiguating BNs in Yorùbá. These include the so-called familiarity and uniqueness conditions (Roberts, 2003; Russell, 1905; Abbott, 2006), as well as the category of the verb that occurs in the environment of the BN. Familiarity refers to information which is already known from the previous textual context either explicitly or through inference. In Yorùbá, a definite interpretation is permitted when the existence of the entity referred to has been established in the discourse, an indefinite occurs otherwise. In example (2), the first mention of book is indefinite, the second is definite.

(2) Mo ra íwé jún Kólá. L’ójó kejí.  
1SG BUY BOOK FOR KÓLÁ. IN DAY SECOND  
Kólá ti so íwé nù  
KÓLÁ PERF THROW BOOK AWAY  

‘I bought a book for Kólá. By the second day, Kólá had lost the book.’

The uniqueness condition claims that there exists one and only one entity that meets the descriptive content of the BN as in example (3)\(^4\). This entails that the BN will be interpreted as definite and singular.

(3) Oórun máa ní ràn ní ósán  
SUN HAB PROG SHINE IN AFTERNOON  

‘The sun shines in the afternoon.’

The category of verb is also an important contextual element in correctly translating BNs. *Stative* verbs (verbs that describe the state of being or situation such as to own and to feel) introduce the *Generic* description where a noun phrase is used to refer to a whole class as in example (4). *Eventive* verbs (verbs that describe events such as to break and to appear) introduce all other disambiguation patterns as in example (1).

\(^2\) 1st Person Singular (1SG), Perfective (PERF)  
\(^4\) Habitual (HAB), Progressive (PROG)
3 Related work

Traditional evaluation methods like BLEU are inadequate for evaluation of fine-grained discourse phenomena in MT, and various approaches have been explored to alleviate this problem. Guillou and Hardmeier (2016) present the PROTEST pronoun translation test suite. The test suite contains examples of pronoun translation which are known to be challenging for MT systems. Isabelle et al. (2017) present another challenge set for MT. This set consists of a number of human annotated sentences which are designed to probe a system’s capacity to handle various linguistic phenomena (like EXAMPLES). Using the challenge set, Isabelle et al. (2017) present a comparison of SMT and NMT systems for English-French MT which provides a fine-grained exploration of the strengths of NMT, as well as insight into linguistic phenomena that typically present difficulties for NMT models.

Sennrich (2016) assess the grammaticality of the output of a character-level NMT system by evaluating the MT model’s capacity to correctly rank contrastive pairs of pre-existing translations, one of which is correct and the other one incorrect. This approach has also been applied to lexical disambiguation of English-German MT (Gonzales et al., 2017). Bentivogli et al. (2016) explore automatic detection and classification of translation errors based on manual post-edits of MT output both for SMT and NMT systems. They use a classification that evaluated outputs for morphological, lexical, and word order errors which was a simplification of those used in Hjerson (Popović, 2011). Hjerson detects word level error classes: morphological errors, re-ordering errors, missing words, extra words and lexical errors.

Recently, neural models have been evaluated for syntactic competence. For instance, Linzen et al. (2016) probe the ability of LSTM models to learn English subject-verb agreement. When provided explicit supervision, LSTMs were able to learn to perform the verb number agreement task in most cases, although their error rate increased on particularly difficult sentences. NMT systems have also been evaluated for morphological competence while translating from English to a morphologically rich language (Burlot and Yvon, 2017).

Certain linguistic phenomena have also been tested across language families. For instance, for four language families: Slavic, Germanic, Finno-Ugric and Romance, the best NMT system outperformed the best phrase-based SMT system for all language directions to English (Toral and Sánchez-Cartagena, 2017). The NMT systems produced fluent and more accurate inflections and word order but performed poorly when translating long sentences (Vanmassenhove et al., 2019; Bentivogli et al., 2016). Morphologically rich languages have also been shown to have more fluent outputs (Klubička et al., 2017; Toral and Sánchez-Cartagena, 2017; Popović, 2018). These studies have used metrics such as BLEU (Papineni et al., 2002b), HTER (Snover et al., 2006), TTR (DARELEY, 1959), YULE (Yule, 2014) to evaluate the output of MT models for fluency and adequacy.

4 Dataset

We use the Yorùbá Bible Bíbélì Mímó ní Èdè Yorùbá Òde-Òní (BMEYO) and the New International Version (NIV) English Bible.

4.1 Bible Data

We crawled the BMEYO Yorùbá Bible from the public website Biblica. This version is the modern translation of the Yorùbá Bible and is the closest equivalent to the English NIV Bible, according to Biblica. We thus use the NIV English translation with the Bible to create our parallel data. We organize the Bible according to their verses. In Table 1, we show an example verse from our Bible dataset.

| Data | Scripture |
|------|-----------|
| BMEYO | Ìgbà láti pa àti ìgbà láti mú láràdá ìgbà àtì wọ lule àtì ìgbà láti kò |
| NIV  | a time to kill and a time to heal. a time to tear down and a time to build. |

Table 1: A description of Ecclesiastes Ch. 3, Verse 3 for the BMEYO. (NIV English Bible translation)

| Data | #TOK | #SENT | #TTR |
|------|------|-------|------|
| BMEYO | 793,870 | 38,149 | 25.5 |

Table 2: A statistical description of the Yorùbá (source) data. #TOK refers to number of tokens, #SENT is number of sentences, and TTR is type token-ratio.

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5 https://www.Bible.com/versions/911-ycb-bibeli-mim-ni-ede-yoruba-ode-oni
4.2 Data Preprocessing

The Yorùbá Bible is based on old Bible manuscripts. A total of 16 verses which were included in early English Bible versions like the King James Bible but which were omitted from later versions are still part of the Yorùbá Bible. Therefore, we start data preprocessing by adding these missing verses into our English NIV Bible to make it equivalent with the Yorùbá text. Those verses were footnotes in the English NIV. In addition, the book of Third John has 15 verses in the Yorùbá Bible but 14 verses in the English NIV. The 15th verse in the Yorùbá is a part of 14th verse in the English Bible. As a result, we combine verse 15 into verse 14, as it is in the English NIV. The aligned dataset can be found on GitHub at https://github.com/UBC-NLP/africaNLP2021.

Next, we tokenized the English data using SpaCy. SpaCy currently does not provide a tokenization package for Yorùbá, so we used the whitespace tokenizer for all the Yorùbá data. We use python scripts to ensure the punctuations is appropriately tokenized. Next, we convert all words to lowercase in order to alleviate data sparsity. We also split words using Byte Pair Encoding (BPE) (Sennrich et al., 2015). In low-resource settings, large vocabularies result in the representation of low-frequency (sub)words as BPE units which affects the ability to learn good high-dimensional representations (Barone et al., 2017). Thus, we choose smaller merge operations and varied the number of merge operations from 10,000 to 30,000. Finally, we split the dataset into training, validation, and test sets using an 80%-10%-10% standard split.

5 Methods

We train 3 sentence level models: SMT, BiLSTM, and Transformer models to translate from Yorùbá to English. We choose English as our target language because we are interested in analyzing how ambiguous BNs in Yorùbá are translated into English where (i.e., in English) nouns are typically marked both for number and determinacy. The hyperparameters and training procedure are described in the next subsections.

5.1 SMT

We use the Moses statistical translation system for our SMT model. We apply tokenization, true casing, and perform word alignment on the parallel data using GIZA++ (Och and Ney, 2003). The word alignments were used to extract phrase-paired translations and calculate probability estimates (Koehn et al., 2007). We used KENLM (Heafield, 2011) to train and query a LM for English. KENLM is a library implemented for efficient language model queries, reducing both time and memory costs, and is integrated into Moses. The decoder uses this LM to ensure a fluent output of the target language, in our case, English. We used the validation sets of our parallel data for the final tuning process just before we perform the blind testing.

5.2 BiLSTM

We use a Sequence to Sequence (Seq2Seq) BiLSTM with attention model. Our best BiLSTM model has an embedding layer with 1,024 dimensions, and 2 encoder and decoder layers each. We use the Adam optimizer with a learning rate of 5e-4 and a batch size of 32. For regularization, we use a dropout of 0.2.

| Hyperparameter       | Values       |
|----------------------|--------------|
| encoder layers       | 2, 3, 4, 6, 8|
| decoder layers       | 2, 3, 4, 6, 8|
| embedding dimension  | 256, 512, 1024|
| batch sizes          | 32, 64, 128  |
| number of tokens     | 4000, 4096   |
| dropout              | 0.2, 0.3, 0.4, 0.6, 0.8 |

Table 3: Hyperparameter settings for tuning BiLSTM and Transformer models.

5.3 Transformer

For the transformer model, we use 5 layers with 8 attention heads in both encoder and decoder. We use embedding dimension with 1,024 units. We express our batch size in number of tokens, and set it to 4,096. Detailed hyperparameter settings is available in Table 4.

| Hyperparameter     | Values |
|--------------------|--------|
| encoder layers     | 2, 3, 4, 6, 8 |
| decoder layers     | 2, 3, 4, 6, 8 |
| embedding dimension| 256, 512, 1024 |
| batch sizes        | 32, 64, 128 |
| number of tokens   | 4000, 4096 |
| dropout            | 0.2, 0.3, 0.4, 0.6, 0.8 |

Table 4: Hyperparameter settings for tuning Transformer models.
We evaluate the output of our models using BLEU. We varied the number of BPE vocabulary size. Training. We train the model with fairseq toolkit (Papineni et al., 2002b). We use BLEU score because it is the most commonly used metric for MT evaluation. Table 5 shows our n-gram precision figures from 1 to 4-grams and our overall BLEU score. Our transformer model outperforms the BiLSTM and SMT models respectively.

Our transformer model outperforms the BiLSTM models since the size of data is small, we experimented with different hyperparameter values to ensure optimization of our models. Since the size of data is small, we used fewer layers, and smaller batch sizes as referenced in literature (Sennrich and Zhang, 2019; Nguyen and Chiang, 2017). A full range of hyperparameters and values are in Table 3.

Vocabulary Size. We varied the number of BPE merge operations from 10,000 to 30,000. Our optimal models used 10K merge operations.

Training. We train the model with fairseq toolkit for 7 days, on 1 GPU, and choose best epoch on our development set, reporting performance on TEST.

6 Evaluation

In this section, we first evaluate using BLEU. We provide details of this part of the evaluation in Section 6.1. Next, we provide details on our approach to evaluating BNs in Section 6.2.

6.1 Model Performance

We evaluate the output of our models using BLEU (Papineni et al., 2002b). We use BLEU score because it is the most commonly used metric for MT evaluation. Table 5 shows our n-gram precision figures from 1 to 4-grams and our overall BLEU score. Our transformer model outperforms the BiLSTM and SMT models respectively.

We give examples of the output from each model and the gold data in Table 6.

| Hyperparameter       | Values          |
|----------------------|-----------------|
| adam-betas           | (0.9, 0.98)     |
| clip-norm            | 0.0             |
| learning rate        | 5e-4            |
| learning rate scheduler | inverse square root |
| warmup-updates       | 4000            |
| dropout              | 0.3             |
| weight-decay         | 0.0001          |
| criterion            | label smoothed cross entropy |
| label-smoothing      | 0.5             |
| encoder-layerdrop    | 0.2             |
| decoder-layerdrop    | 0.2             |

Table 4: Hyperparameters for Transformer model

5.4 Hyperparameters, Vocab. & Training

Hyperparameters. We experimented with different hyperparameter values to ensure optimization of our models. Since the size of data is small, we used fewer layers, and smaller batch sizes as referenced in literature (Sennrich and Zhang, 2019; Nguyen and Chiang, 2017). A full range of hyperparameters and values are in Table 3.

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| SMT   | 1-gram | 2-gram | 3-gram | 4-gram | BLEU  |
|-------|--------|--------|--------|--------|-------|
|       | 62.00  | 47.97  | 38.68  | 31.92  | 33.01 |

| BiLSTM | 1-gram | 2-gram | 3-gram | 4-gram | BLEU  |
|--------|--------|--------|--------|--------|-------|
|        | 62.97  | 49.21  | 40.08  | 33.43  | 33.44 |

| Transformer | 1-gram | 2-gram | 3-gram | 4-gram | BLEU  |
|-------------|--------|--------|--------|--------|-------|
|             | 66.27  | 53.42  | 44.45  | 37.68  | 37.93 |

Table 5: Model performance at 1-4 grams with final column showing BLEU score as given by the sacrebleu (Post, 2018).

| Gold Data | SMT   | BiLSTM | Transformer |
|-----------|-------|--------|-------------|
| as in the days when you came out of egypt, i will show them my wonders. | like the day she came up out of egypt, i will show wonders known him. | as soon as he came out of egypt, i will show him all the wonders he has done. | like the day he came up out of egypt, i will show him the wonders. |
| rescue me from the mouth of the lions; save me from the horns of the wild oxen. | the lord delivered my life from the lions; rescue me from the horns of the wild ox. | deliver my life from the lion’s hands; deliver me from the hand of the wild ox. | rescue my life from the lion; rescue me from the horns of the wild ox. |
| so now the lord has put a lying spirit in the mouths of all these prophets of yours. the lord has decreed disaster for you. | so the lord has put a lying spirit in the mouths of all your prophets. the lord has decreed disaster for you. | so the lord has put a lying spirit in the mouths of all these prophets of yours. the lord has decreed disaster for you. | so the lord has put a lying spirit in the mouths of all these prophets of yours. the lord has decreed disaster for you. |

Table 6: A comparison of the gold data with the output of our models.
inite singular, indefinite plural, definite singular and definite plural. We do this both for the gold standard target data and for the output of our MT systems, and compare the distribution of categories in the MT output to the category distribution in the English gold standard data. The annotation was performed by a linguist who is also a native speaker of Yorùbá.

| Category       | Description                                      |
|----------------|--------------------------------------------------|
| Generic noun   | noun refers to a kind or class of individuals.   |
| Indefinite Singular noun | noun refers to a single non-specific object         |
| Indefinite Plural noun       | noun refers to multiple non-specific objects         |
| Definite Singular noun       | noun refers to a single specific object            |
| Definite Plural noun         | noun refers to multiple specific objects           |

Table 7: Noun Categories when translating from Yorùbá to English

Determining the correct category for the translation of a BN requires us to control for the following contextual information: type of verb (STATIVE versus EVENTIVE); the discourse context (e.g. the preceding sentence, the familiarity constraint); and real-world knowledge (which may trigger the uniqueness constraint). E.g. Yorùbá words (ọba king, ọlọrun god) should always be translated into definite singulars because Yorùbá speakers commonly use them to refer to specific entities.

### 6.3 Evaluation of Bare Noun Disambiguation

To measure how well our models translate BNs, we randomly select 100 sentences and evaluate the percentage of correct BN translations for each model. The 100 sentences selected contained 236 occurrences of BNs. There were 9 indefinite plural, 46 indefinite singular, 35 definite plural, 103 definite singular and 43 generic examples in this randomly selected set. We perform a detailed error analysis on the 100 sentences for each case of incorrect BN translation.

We assemble the type of errors found in the translation output into a confusion matrix that captures the behaviour of the 3 models in Figure 1. Each row in the confusion matrix represents one of our 5 noun categories and each row adds up to 100%. The dark blue coloured boxes represent the correctly translated values in percentages. The light blue boxes are the incorrectly translated categories that fell within one of the 5% categories. The column "others" contain incorrectly translated choices outside the 5 categories. We discuss these type of errors in detail in 6.4.

#### 6.4 Detailed Error Analysis

The results show that the transformer model outperforms the SMT and BiLSTM models for all categories except the indefinite plural category where the SMT outperforms the Transformer model. The
BiLSTM also outperforms the SMT for 3 categories.

**How the models handle indefinites.** In the context of indefinites, we found that all 3 models achieved low accuracy scores. We assume this to be the case because fewer cases of indefinites are often reported in languages like Yorùbá that lack overt definite and indefinite markers and this will be represented in the data we used for training. Languages like Yorùbá that do not have overt definite and indefinite determiners are ambiguous between definite and indefinite readings. Indefinites are blocked when the common ground establishes the uniqueness, or familiarity of the set denoted by the noun (Dayal and Sağ, 2019). It is expected that indefinites can occur everywhere else. However, in texts such as these, context introduces either familiarity or uniqueness therefore reducing the occurrence of indefinites.

**How the models handle definites.** There were 138 BN instances that translated as definites in the set we evaluated. This is due to the aforementioned system of disambiguation that assigns BNs to the definite class if they occur in an environment of uniqueness or familiarity. There are also certain words that have an inherent unique meaning due to cultural beliefs of Yorùbá people. Titles such as oba king, olúwa lord and many more often have a definite translation because it is culturally believed for instance that only one king can rule a domain. The models show an improvement in translating definites when compared to indefinites.

**How the models handle generics.** The Transformer model outperforms the BiLSTM and SMT models for this category while the BiLSTM outperforms the SMT.

### 6.4 Error Analysis

We focus on other errors, that is those errors presented in the "others" category/column in Figure 1. For this class of errors, the wrongly translated BN did not translate into one of definite singular or plural, indefinite singular or plural, generic or BN category. We therefore evaluate the errors found in the sentences. For the sentences evaluated, we focus only on errors that involve nouns and determiners and ignore errors relating to other classes of words. This means that if a sentence had errors with, for example, verbs or adjectives, we ignored these errors. We categorize the errors we found and provide examples errors for each category in the SMT and NMT models in Table 8. We **bold** face relevant words and phrases occurring in the gold data that had errors in the model output.

**Missing word.** Outputs with missing nouns or determiners are classified under this category.

**Wrong word or spelling.** Wrong use of determiners or incorrect nouns belong to this category. We also classify wrong spellings, poorly inflected forms of the noun and unknown words under this category.

**Grammaticality.** We categorize both syntactic and semantic errors here. Wrong tense or aspect, incorrect number, poor punctuation, and lack of coherence are categorized under this class.

**Wrong word order or category.** If the order of the noun and determiner is wrong, even if the determiner and nouns are correct, we classify this as an error. We also include instances where the order of the noun and determiner occurs inappropriately, either before the verb or any other category. We found that some instances require both word level and phrase level order errors. In the case of word level order errors, we can generate a correct sentence by moving individual words, independently of each other, whereas for a phrase level order error, blocks of consecutive words should be moved together to form a right translation. In addition, this category includes instances in which a different type is used instead of a noun or determiner.

In evaluating each category, we do not consider correct synonyms as errors.

### 6.5 Word-Level BN Disambiguation

We randomly select 10 nouns that occur as BNs in the test data and check how well the 3 models disambiguate these words. We use the following words: ilu town, iwe book, ile house, okùnrin male, obìnrin female, aso clothing, ilè land, oba king, àlùfáà priest and baba father.

We then calculate the percentage of correct translations of these BNs in the test set. We use the English gold data to determine the correct disambiguation and compare each instance of the BNs with the corresponding occurrence in the gold data.

Our analysis in Figure 2 shows that the transformer model performs better in disambiguating the BNs selected. The transformer model achieves **67.85%** accuracy while the BiLSTM
Table 8: Example of errors for the three models under each error category we described. The English Gold is the BLEU scores as well as a positive correlation between disambiguation accuracy, and correctly disambiguated BNs. We found a positive correlation between disambiguation accuracy, and correctly disambiguated BNs compared with incorrect disambiguated BNs. We found a positive correlation between disambiguation accuracy, and BLEU scores as well as a positive correlation between number of occurrences of a category and the accuracy in translation.

We also found the transformer outperforming the SMT and BiLSTM models in correctly translating BNs and found that all 3 models best performed in translating a BN in Yorùbá into an definite singular in English. This finding corroborates research that predicts that languages which lack overt definite and indefinite markers have larger cases of definites, and findings within the MT community that MT models improve with more data. We also analyzed the type of errors our systems produce. We identified cases of missing words, wrong word or spellings, grammaticality issues, and word-order errors. We found that even when certain BNs have been correctly categorized by the models, the models still had semantic, and or syntactic errors.

To further probe the capacity of SMT and NMT models in disambiguating BNs, we can improve the SMT and NMT models with back-translation, cross-lingual word embeddings, larger training data, among other approaches and perform human based evaluations on the entire quality of the MT output. Standard test sets can also be developed to aid automatic comparison of human evaluations and machine based evaluations. In addition, the Yorùbá data we used for this work is a translated document; a translation from English to Yorùbá and it will be interesting to use a text originally written in Yorùbá but translated to English for this experiment.
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References

Barbara Abbott. 2006. Definite and indefinite. Encyclopedia of language and linguistics, 3(392):99.

Antonio Valerio Miceli Barone, Jindřich Helcl, Rico Sennrich, Barry Haddow, and Alexandra Birch. 2017. Deep architectures for neural machine translation. arXiv preprint arXiv:1707.07631.

Rachel Bawden, Rico Sennrich, Alexandra Birch, and Barry Haddow. 2017. Evaluating discourse phenomena in neural machine translation. arXiv preprint arXiv:1711.00513.

Luisa Bentivogli, Arianna Bisazza, Mauro Cettolo, and Marcello Federico. 2016. Neural versus phrase-based machine translation quality: a case study. arXiv preprint arXiv:1608.04631.

Franck Burlot and François Yvon. 2017. Evaluating the morphological competence of machine translation systems. In Proceedings of the Second Conference on Machine Translation, pages 43–55.

Greg N Carlson. 1989. On the semantic composition of English generic sentences. In Properties, types and meaning, pages 167–192. Springer.

Marine Carpuat. 2009. One translation per discourse. In Proceedings of the Workshop on Semantic Evaluations: Recent Achievements and Future Directions (SEW-2009), pages 19–27.

Lisa Lai-Shen Cheng and Rint Sybesma. 1999. Bare and non-so-bare nouns and the structure of np. Linguistic inquiry, 30(4):509–542.

Gennaro Chierchia. 1998. Reference to kinds across language. Natural language semantics, 6(4):339–405.

Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2017. Word translation without parallel data. arXiv preprint arXiv:1710.04087.

FREDERIC L. DARLEY. 1959. Certain language skills in children: Their development and interrelationships. Pediatrics, 23(4):819–819.

Veneeta Dayal and Yaşımur Sağ. 2019. Determiners and bare nouns. Annual Review of Linguistics, 6.

Annette Rios Gonzales, Laura Mascarell, and Rico Sennrich. 2017. Improving word sense disambiguation in neural machine translation with sense embeddings. In Proceedings of the Second Conference on Machine Translation, pages 11–19.

Liane Guillou and Christian Hardmeier. 2016. Protest: A test suite for evaluating pronouns in machine translation. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 636–643.

Liane Guillou, Christian Hardmeier, Preslav Nakov, Sara Stymne, Jörg Tiedemann, Yannick Versley, Mauro Cettolo, Bonnie Webber, and Andrei Popescu-Belis. 2019. Findings of the 2016 wmt shared task on cross-lingual pronoun prediction. arXiv preprint arXiv:1911.12091.

Christian Hardmeier. 2012. Discourse in statistical machine translation: A survey and a case study. Discours.

Kenneth Heafield. 2011. Kenlm: Faster and smaller language model queries. In Proceedings of the sixth workshop on statistical machine translation, pages 187–197.

Pierre Isabelle, Colin Cherry, and George Foster. 2017. A challenge set approach to evaluating machine translation. arXiv preprint arXiv:1704.07431.

Marcin Junczys-Dowmunt, Tomasz Dwojak, and Hieu Hoang. 2016. Is neural machine translation ready for deployment? A case study on 30 translation directions. arXiv preprint arXiv:1610.01108.

Filip Klubička, Antonio Toral, and Víctor M Sánchez-Cartagena. 2017. Fine-grained human evaluation of neural versus phrase-based machine translation. The Prague Bulletin of Mathematical Linguistics, 108(1):121–132.

Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, et al. 2007. Moses: Open source toolkit for statistical machine translation. In Proceedings of the 45th annual meeting of the association for computational linguistics companion volume proceedings of the demo and poster sessions, pages 177–180.

Manfred Krifka. 2003. Bare nps: kind-referring, indefinites, both, or neither? In Semantics and linguistic theory, volume 13, pages 180–203.

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2017. Unsupervised machine translation using monolingual corpora only. arXiv preprint arXiv:1711.00043.

Richard K Larson. 1985. Bare-np adverbs. Linguistic inquiry, 16(4):595–621.

Tal Linzen, Emmanuel Dupoux, and Yoav Goldberg. 2016. Assessing the ability of lstms to learn syntax-sensitive dependencies. Transactions of the Association for Computational Linguistics, 4:521–535.

Ruslan Mitkov. 1999. Introduction: special issue on anaphora resolution in machine translation and multilingual nlp. Machine translation, pages 159–161.

Toan Q Nguyen and David Chiang. 2017. Transfer learning across low-resource, related languages for neural machine translation. arXiv preprint arXiv:1708.09903.

Franz Josef Och and Hermann Ney. 2003. A systematic comparison of various statistical alignment models. Computational linguistics, 29(1):19–51.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002a. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.
Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002b. 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.

Maja Popović. 2011. Hjerson: An open source tool for automatic error classification of machine translation output. The Prague Bulletin of Mathematical Linguistics, 96(1):59–67.

Maja Popović. 2018. Language-related issues for nmt and pbmt for english–german and english–serbian. Machine Translation, 32(3):237–253.

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, Belgium, Brussels. Association for Computational Linguistics.

Craige Roberts. 2003. Uniqueness in definite noun phrases. Linguistics and philosophy, 26(3):287–350.

Bertrand Russell. 1905. On denoting. Mind, 14(56):479–493.

Rico Sennrich. 2016. How grammatical is character-level neural machine translation? assessing mt quality with contrastive translation pairs. arXiv preprint arXiv:1612.04629.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2015. Neural machine translation of rare words with subword units. arXiv preprint arXiv:1508.07909.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Controlling politeness in neural machine translation via side constraints. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 35–40.

Rico Sennrich and Biao Zhang. 2019. Revisiting low-resource neural machine translation: A case study. arXiv preprint arXiv:1905.11901.

Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In Proceedings of association for machine translation in the Americas, volume 200. Cambridge, MA.

Antonio Toral and Víctor M Sánchez-Cartagena. 2017. A multifaceted evaluation of neural versus phrase-based machine translation for 9 language directions. arXiv preprint arXiv:1701.02901.

Eva Vanmassenhove, Dimitar Shterionov, and Andy Way. 2019. Lost in translation: Loss and decay of linguistic richness in machine translation. arXiv preprint arXiv:1906.12068.

Elena Voita, Pavel Serdyukov, Rico Sennrich, and Ivan Titov. 2018. Context-aware neural machine translation learns anaphora resolution. arXiv preprint arXiv:1805.10163.

Qiang Wang, Bei Li, Tong Xiao, Jingbo Zhu, Changliang Li, Derek F Wong, and Lidia S Chao. 2019. Learning deep transformer models for machine translation. arXiv preprint arXiv:1906.01787.

C Udny Yule. 2014. The statistical study of literary vocabulary. Cambridge University Press.