Modeling Target-Side Morphology in Neural Machine Translation: A Comparison of Strategies

Marion Weller-Di Marco, Matthias Huck, Alexander Fraser †

Center for Information and Language Processing, LMU Munich

Abstract

Morphologically rich languages pose difficulties to machine translation. Machine translation engines that rely on statistical learning from parallel training data, such as state-of-the-art neural systems, face challenges especially with rich morphology on the output language side. Key challenges of rich target-side morphology in data-driven machine translation include: (1) A large amount of differently inflected word surface forms entails a larger vocabulary and thus data sparsity, which in turn aggravates the learning problem. (2) Some inflected forms of infrequent terms typically do not appear in the training corpus, especially under low-resource conditions, which makes closed-vocabulary systems unable to generate these unobserved variants. (3) Linguistic agreement requires the system to correctly match the grammatical categories between inflected word forms in the output sentence, both in terms of target-side morphosyntactic wellformedness and semantic adequacy with respect to the input.

These challenges can be tackled with dedicated linguistic modeling of morphology on the target language side. Recent research has shown that such modeling considerably improves the machine translation quality of neural systems that are based on shallow-RNN encoder-decoder architectures with attention (Bahdanau et al., 2014). In this paper, we re-investigate two target-side linguistic processing techniques—a lemma-tag strategy (Tamchyna et al., 2017) and a linguistically informed word segmentation strategy (Huck et al., 2017b)—with one of the latest incarnations of neural architectures for machine translation, namely the Transformer model (Vaswani et al., 2017).

Our series of empirical experiments are conducted on an English→German translation task under three training corpus conditions of different magnitudes. We find that the stronger Transformer baseline leaves less room for improvement than the older shallow-RNN encoder-decoder model when translating in-domain. However, we find that linguistic modeling of target-side morphology does benefit the Transformer model when the same system is applied to out-of-domain input text. We also successfully apply our approach to English to Czech translation.

† The first two authors had equal effort. The first author has conducted part of the research for this work while being at ILLC, University of Amsterdam. The second author has conducted the research for this work while employed at CIS, LMU Munich.
1 Introduction

Neural machine translation (NMT) has become state-of-the-art in machine translation in the last years. It has been shown to surpass phrase-based statistical machine translation both with regard to general performance in terms of automatic metrics such as BLEU (Papineni et al., 2002), and also in terms of handling linguistic aspects such as syntax and morphology, see, e.g., Bentivogli et al. (2016). However, despite the increase in performance, standard NMT systems do not make strong use of morphological information, but rather benefit from better access to contextual information in the source and target sentences than was possible in phrase-based statistical machine translation.

Recent research has shown that the integration of linguistic information can further improve the translation quality, with a main focus on the syntactic and morphological levels. For example, Eriguchi et al. (2016) and Bastings et al. (2017) demonstrated the positive impact of integrating source-side syntactic information; Nadejde et al. (2017) showed that using syntactic information on the source and target side of an NMT system leads to improved translation quality. Addressing the morphological level, Tamchyna et al. (2017) and Huck et al. (2017b) presented systems to generate target-side inflected forms, resulting in improved translation quality for the respective settings.

A major morphological problem in many applications of natural language processing is the lack of generalization when only looking at surface forms as they appear in a text: inflectional variants of the same lemma are not recognized as closely related, but are treated as completely different words, which is obviously ineffective. In particular for morphologically complex languages with many surface forms, the richness of surface forms increases the vocabulary size, and subsequently leads to data sparsity problems. Furthermore, when translating into a language with complex inflectional morphology, there is the problem of selecting the correct inflection from the set of all possible inflections that may or may not have been observed in the training data. In addition to inflection, there is the issue of productive word formation, i.e., the creation of potentially new complex words from observed components. To address the range of problems that comes along with rich target-side morphology, a strategy that

- introduces a more general, effective and linguistically sound representation, addressing the issue of generalization, and
- allows for the generation of new forms, ideally according to linguistic principles

constitutes a promising and powerful tool to handle translation into morphologically complex languages.

In this paper, we present both a knowledge-rich and a knowledge-poor approach to handle target-side morphology, and explain the linguistic intuitions and pros and cons of the two approaches versus a linguistically uninformed method (Byte Pair Encoding) with respect to generalization. We additionally highlight the important issue of the creation of novel surface words (words which were not seen in the
training data), showing how and where this can occur in both the knowledge-rich and the knowledge-poor approaches. Our analysis shows that we can achieve linguistic generalization through the use of the two presented knowledge-rich and knowledge-poor approaches, and that this outcome is particularly strong in out-of-domain translation scenarios.

1.1 Outline

We give an overview of the problem in Section 2, briefly introducing the approaches compared in this paper, and then describe our two strategies to model target-side morphology in detail – the generation of inflected forms from an abstract representation of lemmas and tags in Section 3, and target-side word segmentation in Section 4. In our experiments in Section 5, the lemma-tag and the segmentation systems are first compared on the English–German language pair for three corpus settings, namely with small, medium, and large training data, using the Transformer NMT model. The systems are applied to in-domain test data (news text), and then analyzed in an out-of-domain context (medical domain). Next, we compare the same strategies within another neural model, a shallow-RNN encoder-decoder translation system, since this model was used in prior work on target-side morphology in NMT. Further analysis and discussion are provided in Sections 6 and 7. We also adapt the strategies to another language pair, English–Czech in Section 8, where we find that large gains are achieved when only small training data is available. In Section 9, we review related work before concluding the paper in Section 10.

2 Overview: Target-side morphology in neural machine translation

Neural machine translation (NMT) is a very successful approach to translation, and has recently resulted in large gains in translation quality, particularly when applied to very large training data sets. Two prominent examples of popular models are shallow recurrent neural network encoder-decoder architectures with attention (Bahdanau et al., 2014), and the Transformer model (Vaswani et al., 2017), which uses self-attention instead of recurrence.

For NMT systems, the overall vocabulary size can be problematic – an unrestricted vocabulary results in memory problems and intractable training times. A common approach to restrict the vocabulary size in NMT has been presented by Sennrich et al. (2016). They adopt a technique in the manner of the Byte Pair Encoding (BPE) compression algorithm (Gage, 1994) in order to segment words into smaller sub-word units. The BPE word segmenter conceptionally proceeds by first splitting all words in the whole corpus into individual characters. The most frequent adjacent pairs of symbols are then consecutively merged, until a specified limit of merge operations has been reached. Merge operations are not applied across word boundaries. The merge operations learned on a training corpus can be stored and applied to other data, such as test sets.

While this strategy has been shown to be effective, it is not linguistically informed, and thus leads to non-optimal splittings. An example of a non-optimal splitting is a
splitting along non-linguistic boundaries which blocks linguistic productivity. Furthermore, BPE does not offer a satisfactory solution to another important problem arising when translating into a morphologically rich language – namely the selection or generation of correctly inflected surface forms given the sentence context.

Recently, linguistically motivated strategies have been proposed to address the problems of obtaining a manageable vocabulary size while not losing coverage (Ataman et al., 2017; Ataman and Federico, 2018), as well as handling target-side inflection for morphologically rich languages (Burlot et al., 2017; García-Martínez et al., 2017; Passban et al., 2018; Conforti et al., 2018). In this paper, we present a case study that contrasts two conceptually similar strategies, of which one makes heavy use of linguistic resources such as parse information and a tool for morphological analysis and generation (Tamchyna et al., 2017), whereas the other approach is comparatively knowledge poor, using only a stemmer (Huck et al., 2017b).

**Knowledge-rich approach.** Tamchyna et al. (2017) replace inflected word forms on the target side to a pair of lemma and morphological tag in the training data of NMT systems from the language pairs English–Czech and English–German. The output of these systems is re-inflected by generating inflected forms from the tag-lemma pairs in a deterministic post-processing step. Reducing inflected word forms to lemmas and a comparatively small set of tags greatly decreases the number of observed word types in the training data, while the morphological tags allow for meeting agreement constraints in the generation step.

**Knowledge-poor approach.** Huck et al. (2017b) propose a segmentation strategy that separates inflectional suffixes from the word stems, as well as a linguistically sound splitting of complex stems, e.g. the handling of prefixes/suffixes and compound splitting. After translation, the components are simply put back together to form inflected target-language words.

**Differences.** Both strategies apply the concept of reducing inflected word forms to stems during the training and translation process and a post-processing step to obtain inflected surface forms, leading to an improvement in the respective studied translation tasks. There are two main differences between the two approaches: (i) the use of explicit linguistic information (i.e. tags annotated with morphological features) and morphological resources in Tamchyna et al. (2017), in contrast to the comparatively resource-poor strategy without explicit generation step in Huck et al. (2017b); and (ii) the handling of sub-words through a more sophisticated segmentation approach by Huck et al. (2017b), which is not addressed by Tamchyna et al. (2017).

The comparison between these two strategies looks at the performance of different training data sizes for an English–German news translation task, and the application to out-of-domain test sets (medical domain). They are also applied to English–Czech.
Table 1. Translation output in lemma-tag format and the resulting inflection for the input sentence “the EU commission wants to double the limits for mercury in large predatory fish . . .”

| Tag   | Lemma       | Inflected Form | Gloss  |
|-------|-------------|----------------|--------|
| <+ART><Fem><Nom><Sg><St> | die<Def> | die | the |
| <+NN><Fem><Nom><Sg><NA> | EU-<TRUNC>Kommission | EU-Kommission | EU commission |
| <+V><1><Sg><Pres><Ind> | wollen | will | wants |
| <+ART><NoGend><Acc><Pl><St> | die<Def> | die | the |
| <+NN><Fem><Acc><Pl><NA> | Grenze | Grenzen | limits |
| [APPR-Acc] | für | für | for |
| <+NN><Neut><Nom><Sg><NA> | Quecksilber | Quecksilber | mercury |
| [APPR-Dat] | in | in | in |
| <+ADJ><NoGend><Dat><Pl><St> | groß<Pos> | großen | large |
| <+NN><Masc><Dat><Pl><NA> | Raub<NN>Fisch | Raubfischen | predatory fish |
| <+V><Inf> | verdoppeln | verdoppeln | double |

3 Knowledge-rich approach: The lemma–tag strategy

The approach for generating inflected forms from pairs of lemmas and morphological tags consists of two steps: translation into an abstract representation and generation of inflected forms. It essentially follows the concept presented by Tamchyna et al. (2017).

To build the translation model, inflected surface forms in the training data, e.g. the adjective form grünes (green), are replaced by an abstract representation of pairs of lemmas and tags annotated with the respective morphological features, e.g. grün + ADJ-Neut.Acc.Sg.Wk. After translation, the system output is re-inflected in a deterministic post-processing step, where the lemma-tag pairs are transformed into inflected surface forms by means of a morphological resource (e.g. grün + ADJ-Neut.Dat.Sg.Wk → grünem).

As the lemma-tag pairs exactly correspond to the surface forms, there is no loss of information. At the same time, a translation model trained on this data representation has access to the more general lemma in combination with flat syntactic information in the form of the morphologically annotated tags.

1 The main difference to the work by Tamchyna et al. (2017) is the representation of the source-side data: here, we use plain English on the source side for a better comparability with the target-side segmentation approach, whereas a sequence of tag-lemma was used by Tamchyna et al. (2017) for the English→German experiment.
3.1 Abstract representation

To prepare the training data for the lemma-tag strategy, information obtained from a parser is combined with the morphological tool SMOR \cite{Schmid2004}, a finite-state based morphological resource to analyze and generate word forms. SMOR is used to obtain the lemma of a surface form, such as $\text{Bäume}_{\text{Inflected}} \rightarrow \text{Baum}_{\text{Lemma}} (\text{treespl}/\text{treesg})$. As inflected word forms on their own can be ambiguous (for example, $\text{Bäume}$ has the possible case values nominative, accusative and genitive), a morphological analysis based on SMOR alone, i.e. without sentence context, is not sufficient. Thus, the German data is parsed with BitPar \cite{Schmid2004} in order to obtain the morphological annotation, which is used as basis for the morphological tag, while SMOR only provides the lemma of a word.

While the reduction of inflected words to lemmas decreases the vocabulary count, a further reduction by means of BPE is still required in order to reach the desired vocabulary size. The lemma-tag strategy only addresses inflected forms, whereas other words such as proper names, which contribute considerably to the vocabulary count, remain unchanged. (Table 12 gives an overview on the vocabulary size of the baseline vs. the lemma-tag representation.) Furthermore, BPE segmentation is applied to both the source and the target data in order to also reduce the vocabulary on the source-side.

3.2 Inflection

Table 4 illustrates the post-processing step for the generation of inflected forms: the left side shows the tag-lemma sequences output by the translation system, based on which inflected forms are generated using the morphological tool SMOR. The tags contain all relevant features for nominal inflection (gender, case, number, strong/weak) and verbal inflection (person, number, tense, mood), and in combination with the lemma, the inflected form is unambiguously defined.

3.3 Generation of new forms and word formation

The lemma-tag strategy addresses some of the main problems in NMT: vocabulary size and the accompanying lack of generalization in morphologically rich languages, and the selection of context-appropriate forms. By representing inflected forms as a pair of lemmas and tags, the vocabulary size can be considerably reduced in a linguistically sound way, and the translation system can generalize over inflectional variants. The generation step makes use of the explicit linguistic information contained in the morphologically annotated tags, such that the inflected forms fit into the sentence context and morpho-syntactic agreement constraints are met.

\footnote{The parse structure itself is not needed; even though it could make for an interesting addition, for example building on the work by \cite{AharoniGoldberg2017} who use linearized constituent trees on the source-side of an NMT system.}

\footnote{If there are orthographic variants the most frequent form according to a monolingual word list is chosen.}
In particular, it is possible to generate inflectional variants not occurring in the training data. While this is to a certain extent also possible with BPE splitting, the lemma-tag approach enables a systematic generation, whereas generation based on BPE segments depends on “lucky splitting” into lemma and suffix and “lucky recombination” into a valid and contextually fitting word form. Furthermore, BPE segmentation cannot handle non-concatenative operations.

While the lemma-tag strategy does not explicitly address word formation, in some cases there are indirect benefits coming from the lemma-internal representation, namely an analysis in terms of derivation and word formation, as can be seen in the example below:

Planetenbewegungen (‘planetary motion’)

\[
\begin{array}{c}
\text{Planet}\langle\text{NN}\rangle \text{bewegen}\langle\text{V}\rangle \text{ung}\langle\text{SUFF}\rangle \langle+\text{NN}\rangle \langle\text{Fem}\rangle \langle\text{Gen}\rangle \langle\text{Pl}\rangle \\
\text{planet}_{\text{NN}} \text{ move}_{\text{V}} \text{ ment}_{\text{SUFF}}
\end{array}
\]

While the derivational information is not actively used in the translation system, the structure of the lemma representation can have an indirect benefit by normalizing components of morphologically complex words such as compounds. In the example above, for instance, the modifier \textit{Planeten} is replaced by the lemma \textit{Planet}, i.e. dropping the transitional element -\textit{en}. Similarly, the verb stem \textit{bewegen} is expanded to the full form \textit{bewegen} (to \textit{move}). Thus, the BPE segmentation process does not have to deal with transitional elements or other variation, but can benefit from a consistent representation between all occurrences of a word or sub-word. In particular, the normalization to lemmas in the modifier position is important in the case of \textit{Umlautung}, such as the change of e.g. \textit{a} → \textit{ä} between different inflected forms, which is a non-concatenative process that cannot be modeled by segmentation-based approaches such as BPE or our knowledge-poor approach. This idea will be further discussed in Section 6, based on the examples given in Tables 10 and 11.

4 Knowledge-poor approach: The word segmentation strategy

The knowledge-poor approach splits words into smaller sub-word units. Previous approaches to sub-word NMT have followed the same core principle, which limits the set of symbols known to the model, while at the same time allowing for open-vocabulary machine translation. A prominent example is BPE word segmentation. Whereas BPE is purely frequency-driven, we strive to integrate a basic amount of linguistic supervision in order to model target-side morphology. BPE sub-words are often not linguistically sound, but we want the machine translation system to reliably inflect output words. The neural model should be able to learn morphological word formation processes from its training data. Our goal is therefore to provide the model with better morphological guidance through a more linguistically informed word segmentation on the target side of the training corpus.

The first idea behind linguistically informed word segmentation is to separate inflectional suffixes from word stems. The segmentation strategy relies on the very same manually defined suffix detection rules that are in wide-spread use for other
Table 2. German suffixes that the suffix splitter can separate from a word stem.

| Suffixes          |
|-------------------|
| -e, -em, -en, -end, -enheit, -enlich, -er, -erheit, -erlich, -ern, -es, -est, -heit, -ig, -igend, -igkeit, -igung, -ik, -isch, -keit, -lich, -lichkeit, -s, -se, -sen, -ses, -st, -ung |

applications in Natural Language Processing and Information Retrieval that benefit from word stemming. Secondly, the approach targets the issue of productive compounding, a common process in many Germanic languages, by integrating a compound splitter. Suffix splitting and compound splitting are combined in the overall pipeline for linguistically informed word segmentation and cascaded with BPE.

4.1 Linguistically informed word segmentation pipeline

In detail, the overall cascaded pipeline for linguistically informed word segmentation consists of three steps:

1. A suffix splitter is applied that separates common German morphological suffixes from the word stems. The suffix splitter is a modification of the German Snowball stemming algorithm from NLTK[4] As opposed to usual stemming scenarios (Porter, 1980), suffixes are however not discarded, but kept as a detached token; also, different from the stemming algorithm, no modifications are applied to the stem part of the word, such as lowercasing or Umlaut replacement ($ä$, $ö$, $ü$ to $a$, $o$, $u$, etc.). The German Snowball stemming algorithm may internally identify multiple consecutive suffixes of a word, which we decide to keep as separate tokens. For instance, wirtschaftlichen (economical) is segmented into wirtschaft $$lich $$en rather than wirtschaft $$lichen. (The $$ characters are a special marker that we add.) Table 2 lists German suffixes that the suffix splitter can detach from a word stem.

2. Next, the empirical compound splitter as described by Koehn and Knight (2003) is applied. A Perl implementation is part of the Moses toolkit (Koehn et al., 2007). We choose an aggressive configuration of the compound splitter (-min-size 4 -min-count 2 -max-count 999999999) in order to end up with a relatively small token vocabulary. We prevent the compound splitter from segmenting suffix tokens that were separated in the previous step. We also introduce a minor modification as compared to the Moses compound splitting script in standard settings. The standard settings take the filler letters “$s$” and “$es$” into account, which often appear between word parts.

[4] http://www.nltk.org/_modules/nltk/stem/snowball.html
Table 3. Declension of the German noun “Fisch” (English: “fish”) in singular and plural in all four German cases. For this example, the singular genitive and dative cases allow for two valid alternatives each.

|             | Singular | Plural |
|-------------|----------|--------|
| Nominative  | Fisch    | Fische |
| Genitive    | Fisches  | Fische |
| Dative      | Fisch/Fische | Fischen |
| Accusative  | Fisch    | Fische |

in German noun compounding. For better consistency of the compound splitting component with suffix splitting, we additionally allow for more fillers, namely; suffixes, suffixes followed by “s”, and “zu”.

3. The BPE technique is finally applied on top of the suffix-split and compound-split data in order to further reduce the vocabulary size. This last step is conducted only for efficiency reasons in NMT. Suffix splitting and compound splitting alone are not suitable for arbitrary reduction of the vocabulary size. We use “joint” BPE in this work, i.e., the BPE merge operations are learned on a concatenation of the target and source language side of the parallel training corpus.

4.2 Example

To give an example of how the word segmenter operates, we present in Table 3 all declensions of a German noun, Fisch (fish). The suffix splitting component of the word segmenter separates the underlined suffixes from any appearance of an inflected occurrence of that noun in the training corpus. The dative plural German noun Fischen becomes Fisch $$en$$. We insert a space character between the stem and the suffix, and the suffix is prepended with an attached special indicator $$ to enable reversibility, an important aspect for post-processing of the NMT system’s output. Assuming that inflected forms of Fisch are present a couple of times in the training corpus, we can hope for the neural model to learn the word’s inflectional variants from the training data. We also counteract data sparsity, because the stem Fisch is now a separate token that likewise appears in all word-segmented versions of training instances that contained any of the declensions of the noun. Furthermore, if some inflected variant of a different noun was unobserved, but that noun follows a regular inflection pattern, the neural model can in principal be able to generate an unseen combination of stem and suffix. For example, if the dative plural variant of the noun Tag was unobserved, but the model knows from sentence context that an English input word day needs to be translated to a dative plural form, then it can produce the output sequence of tokens Tag $$en$$, resulting in a correct morphological form. Finally, we think that the detached suffix tokens facilitate learning how to produce correct linguistic agreement between output words.
The second cascaded component of the linguistically informed word segmentation pipeline is the compound splitter. We explain the utility of compound splitting by following up on the *Fisch* example. There exist different types of fish, such as *ornamental fish* or *juvenile fish*. These are often expressed as compound in German, e.g. *Zierfisch* or *Jungfisch*. Each of these compounds can be inflected, e.g. *Zierfischen* – *Zierfisch $\$en* after suffix splitting. Compound splitting gives us *#U zier @@ Fisch $\$en*, where “@@” is a standalone compound separator token that we introduce, and “#U” indicates that uppercasing is required when the compound is re-merged from the sub-words (“#L” for lowercasing). The model can now learn to produce new compounds at inference time, such as *#U zier @@ Gegenstand* (ornamental object).

### 4.3 Limitations

For the input sentence *the EU commission wants to double the limits for mercury in large predatory fish* from Table 1, a neural model that was trained with linguistically informed target-side word segmentation outputs the translation: *die EU @-@ Kommission möcht $\$e die #U Grenz $\$e für Quecksilber $\$er in groß $\$en #U Raub @@ Fisch $\$en verdoppeln*.

While this example translation is fluent and adequate, it also highlights drawbacks of the knowledge-poor approach.

The conjugated verb *möchte* is properly split into stem and suffix, but the verb is irregular. The knowledge-rich approach with full morphological analysis would know the lemma *mögen* and combine it with a morphological feature tag, which the morphological generation tool would employ to map the lemma-tag pair to the surface form *möchte* in post-processing. The knowledge-poor segmentation strategy generalizes less well over inflectional variants. This holds not only for verbs, but also for nouns, where the stem may occasionally be altered with a change in case or number, such as *Haus* (*house*) being *Häuser* in plural, or the similar *Umlautung* in *Bäume* → *Baum* that we mentioned in Section 3.3 already.

The noun *Quecksilber* (*mercury/quicksilver*) is segmented because the stemming algorithm’s simple rules have failed to recognize that the suffix is not inflectional in this instance. The system has produced the right output word from its parts, but such flawed splits in the training data most likely hamper the learning of inflectional patterns.

Some shortcomings of our current pipeline would vanish with improved stemming algorithms (Weissweiler and Fraser, 2017) and compound splitting tools. We however believe that the knowledge-rich lemma-tag strategy has some conceptual advantages over plain word segmentation. The linguistically informed word segmentation strategy, in turn, will typically be implementable much more quickly for new languages than the knowledge-rich lemma-tag strategy, because coding stemmer-like rules is much simpler than building a full-fledged morphological analyzer, lemmatizer, and generation tool. Depending on the runtime efficiency of the morphological analysis tool, the training data preparation can also take longer for the lemma-tag strategy.
5 Empirical evaluation: Machine translation experiments

In this section, we present and discuss the results of the two strategies, first in a general-language setting, and then in a cross-domain experiment translating medical data. Additionally, both strategies are repeated with another translation toolkit, the Nematus system.

5.1 Experimental setup

5.1.1 Data

An important question for the evaluation of the two presented strategies is the performance on data sets of different sizes and domains. For the performance on general language, we look at three settings: a small corpus (248,730 parallel sentences), a medium-sized corpus (1M parallel sentences) and a large corpus (1,956,444 parallel sentences), where the small corpus consists of the news-commentary data set, the large corpus combines Europarl with the news-commentary corpus, and the medium corpus is a random subset of Europarl combined with the news-commentary corpus (after filtering, see below). As development and test sets, we use the WMT’15 (dev/validation) and WMT’16 (test) newstest sets.

The presented approaches affect the sentence length: the lemma-tag approach essentially doubles the sentence length by inserting tags, in addition to BPE splitting applied to the tag-lemma pairs; the target-side word segmentation approach also leads to considerably longer sentences than the standard BPE splitting. For efficiency reasons during training, it is common practice to set a maximum sequence length; training sentences longer than that are lost (or partially lost) during training. For this reason, the increased sentence length in the lemma-tag and the segmentation strategy needs to be addressed in the setup of the training data. To ensure that both the baseline system and the linguistically informed systems can make use of all training sentences, the data is prepared in a way that the maximum sentence length can just be set to a high value (or the longest sentence occurring in the corpus) to include all sentences in the training. This is achieved by restricting the sentence length, including BPE segmentation which can result in considerably increased sentence lengths in some cases. To avoid overly long sentences, the training data was first filtered to sentences of length 50, and in a second filtering step, all sentences containing more than 60 words after standard BPE splitting were removed. This second filtering targeted sentences containing mostly foreign language words or characters, being split nearly at character level. Length filtering was only applied to the training data, but not to the development and test data.

5 All corpora are freely available from the WMT shared tasks website at http://www.statmt.org/wmt19/ Shared task BLEU scores can be viewed on the WMT evaluation matrix website at http://matrix.statmt.org/ Bojar et al. (2013) and Bojar et al. (2018) provide the official WMT’15 and WMT’16 shared task results including human evaluation.
Data pre-processing: Baseline. The baseline is a system trained on standard surface forms (tokenized and truecased), segmented with BPE to the configured vocabulary size. The English and German sides were concatenated prior to BPE segmentation in order to have a consistent representation for shared vocabulary between source and target side (also known as “joint” BPE).

Data pre-processing: Lemma-tag strategy. The training data for the lemma-tag strategy was prepared based on data parsed with BitPar (Schmid, 2004) for the morphological features to be annotated to the tags. The lemmas were obtained through analysis with SMOR (Schmid et al., 2004), as described in Section 3.1. While reducing inflected word forms to lemmas and tags decreases the vocabulary of the German data, a further reduction by means of BPE is still required: the lemma-tag strategy addresses only inflected forms, i.e. leaving other words, such as proper names, unmodified. Furthermore, the English side is not affected by the lemma-tag modification. Prior to training the translation model, the German and English sides are thus segmented with BPE until the desired vocabulary size is reached (29,500 merge operations). As for the baseline experiments, the English and German sides are concatenated to enable a consistent representation of shared vocabulary. The abstract representation in SMOR format should not pose a problem, as shared vocabulary mostly consists of named entities that are not subject to the lemmatized representation anyway, but remain in their original format.

Data pre-processing: Segmentation strategy. For the setup with linguistically informed target word segmentation, tokenization and truecasing were the same as for the baseline, except that we additionally applied hyphen splitting on both the source and the target side, which for instance turns EU-Kommission into EU @-@ Kommission. We then applied the full word segmentation pipeline as outlined in detail in Section 4.1 to the German target-language side of the training data. The English source side was BPE-split with the “joint” BPE model. The number of BPE merge operations was set to the same amount that had also been configured for the baseline and for the lemma-tag setup (29,500 merge operations). Also consistent with all other setups in this study, we attach the marker that indicates a BPE segmentation point (for this setup: #) to the right end of the sub-word that appears to the left of the segmentation point. Compound split indicators remain standalone symbols (as in # U Stahl @ Werk; or, with a filler, # U Jahr @es@ Wechsel), which we found to be important for translation quality. The three cascaded splitters can segment single words into fairly long sub-word sequences, such as the sequence # U Neben## ererb @s@ Land @@ Wir## t $$e.

5.1.2 Transformer system configuration
The experiments were carried out using a Transformer NMT model with the Sockeye toolkit (Hieber et al., 2017). Table 4 shows the training hyperparameters. Additional Sockeye configuration options that are not listed have been kept at their defaults. Our configuration settings are a mix of conventional values (Vaswani et al.,
Table 4. Sockeye hyperparameter settings for the Transformer model.

| Parameter                  | Value         |
|----------------------------|---------------|
| encoder                    | transformer   |
| num-layers                 | 6             |
| decoder                    | transformer   |
| label-smoothing            | 0.1           |
| batch-type                 | word          |
| transformer-dropout-act    | 0.1           |
| batch-size                 | 4096          |
| transformer-dropout-attention | 0.1     |
| initial-learning-rate      | 0.0002        |
| transformer-dropout-prepost| 0.1           |
| max-seq-len                | 200           |
| checkpoint-frequency       | 3000          |

Table 5. Results with Transformer for the LemmaTag and Segmentation approaches in comparison to a system trained on surface forms (Baseline) in case-sensitive BLEU. Significant improvements over the baseline (p-value=0.05) are marked with *.

| English–German In-domain Translation | Small | Medium | Large |
|---------------------------------------|-------|--------|-------|
| Transformer BPE Baseline             | 21.5  | 27.4   | 29.0  |
| Transformer LemmaTag                 | 21.9 *| 27.5   | 28.8  |
| Transformer Segmentation             | 22.2 *| 27.0   | 29.0  |

that we have had good experience with when previously building competitive machine translation systems (Huck et al., 2018).

5.2 Experimental results

5.2.1 In-domain translation with a Transformer system

Table 5 shows the results for the baseline, i.e. a system with standard BPE splitting, the lemma-tag system and the system applying target-side segmentation. While the lemma-tag and the segmentation strategies outperform the baseline when trained on the small data set, their performance is at the same level as the baseline for the medium and the large setting.

5.2.2 Out-of-domain translation with a Transformer system

Many translation scenarios involve the handling of low-resource data, where the main difficulty lies in setting up a translation model with only little available domain-specific training data, if at all. In such a situation, the problems caused by rich (target-side) morphology are typically aggravated, as inflectional variants

\[6\] Significance was computed with the script `bootstrap-hypothesis-difference -significance.pl` that is part of the Moses package, available from [https://github.com/moses-smt/mosesdecoder/](https://github.com/moses-smt/mosesdecoder/)
Table 6. Results for the out-of-domain medical test set for the LemmaTag and Segmentation approaches in comparison to a system trained on surface forms (Baseline) in case-sensitive BLEU. Significant improvements over the baseline (p-value=0.05) are marked with *

|                      | Small | Medium | Large |
|----------------------|-------|--------|-------|
| Transformer BPE Baseline | 18.0  | 23.3   | 24.4  |
| Transformer LemmaTag  | 19.0* | 24.2*  | 25.1* |
| Transformer Segmentation | 18.9* | 22.9   | 24.8  |

are less likely to appear in the limited amount of training data and thus cannot be learned and produced by the system.

A domain that differs greatly from general language is the medical domain which has an obvious difference in the used vocabulary. Applying a system trained on general language, but with a component to handle target-side morphology thus constitutes an interesting use case. For this experiment, we use a test set from the project HimL (Health in my Language) consisting of 1931 sentences. This test set consists of data extracted from NHS 24 (the National Health Service) and Cochrane online content. While the NHS data contains health information aimed at the general public, the Cochrane part consists of summaries of scientific studies, and differs considerably from the NHS-based sentences. The German reference translations were obtained by post-editing, with the initial automatic translation created by a Moses phrase-based MT system. Note that this test set has also been standardly used in the biomedical shared tasks at WMT (Jimeno Yépes et al., 2017; Neves et al., 2018), but there large biomedical training data sets were made available, in contrast to our study, which instead looks at the difficult out-of-domain translation task.

Table 6 gives the results for translating data from the medical domain. The lemma-tag strategy as well as the segmentation approach lead to improved results over the baseline system, particularly with the Small training size. Interestingly, the lemma-tag strategy also provides for statistically significant gains for the Medium and Large training sizes. The gains are larger because the translation task is more difficult and thus can benefit more easily from the linguistic information, and the ability to generate new words and word forms. Table 6 in section 7.3 discusses an example translation from the medical domain.

7 http://www.himl.eu/files/himl-test-2015.tgz
8 https://www.cochrane.org/
Table 7. Nematus hyperparameter settings for the shallow-RNN model.

| Parameter          | Value   |
|--------------------|---------|
| vocab size         | 30k     |
| embedding size     | 500     |
| hidden layer size  | 1024    |
| learning rate      | 0.0001  |
| dropout embedding  | 0.2     |
| dropout hidden     | 0.2     |
| dropout source     | 0.1     |
| dropout target     | 0.1     |

5.3 Sanity check: Comparison with a shallow-RNN system

Our previous work showed larger gains when working with shallow-RNN systems for the lemma-tag approach. For this reason, we decided to run experiments applying both strategies using a shallow-RNN translation model and examine these as well.

5.3.1 Shallow-RNN system configuration

The RNN experiments were carried out using the Nematus toolkit \cite{Sennrich2017}. The RNN is shallow, i.e., we use one single hidden layer, not a deep model. Like in the Transformer experiments with Sockeye, for Nematus we again settle on a minor variation of configuration settings that we had already employed in previous work \cite{Huck2017} with a top shared task result \cite{Bojar2018}. Table 7 lists the Nematus hyperparameters used in this set of experiments. Additional Nematus configuration options that are not listed were kept at their default values. We trained with the Adam optimizer \cite{Kingma2015}, a batch size of 128, and, due to memory issues with the increased sentence length, 116 for the lemma-tag experiments.

5.3.2 In-domain translation with a shallow-RNN system

Table 8 shows the results of in-domain translation with shallow-RNN systems. In contrast to the experiments with Transformer, the lemma-tag approach is able to outperform the baseline system for both the Small and Large training data sizes, even though the BLEU difference decreases with increasing training data size. This outcome is not surprising, as linguistic information tends to become less effective if more training data is available. However, even in the setting with nearly 2M parallel sentences, the lemma-tag system still benefits. The results for the segmentation system are again more mixed.

\footnote{For example, \cite{Burlot2016} present a set of experiments with varying training data sizes for a task similar to ours, and report that they see less impact of linguistic modeling with increased training data. The general reasoning behind this observation is that more training data means that the system sees more word forms during training, and thus is able to derive better statistics. As a result, the linguistic modeling, i.e. better generalization, becomes less effective.}
Table 8. Results with *Nematus* for the LemmaTag approach in comparison to a system trained on surface forms (Baseline) in case-sensitive BLEU. Significant improvements over the baseline (p-value=0.05) are marked with *.

|                                | Small | Medium | Large |
|--------------------------------|-------|--------|-------|
| Shallow-RNN BPE Baseline       | 22.1  | 26.4   | 27.5  |
| Shallow-RNN LemmaTag           | 23.4 *| 26.7   | 28.3 *|
| Shallow-RNN Segmentation       | 22.4  | 26.7   | 27.8  |

Table 9. Results for the LemmaTag approach in comparison to a system trained on surface forms (Baseline) in case-sensitive BLEU for medical data (HimL test set). Significant improvements over the baseline (p-value=0.05) are marked with *.

|                                | Small | Medium | Large |
|--------------------------------|-------|--------|-------|
| Shallow-RNN BPE Baseline       | 19.3  | 24.1   | 25.4  |
| Shallow-RNN LemmaTag           | 20.0 *| 24.2   | 26.0 *|
| Shallow-RNN Segmentation       | 19.2  | 23.9   | 24.9  |

5.3.3 Out-of-domain translation with a shallow-RNN system

Table 9 shows the results for the surface system and the lemma-tag system: As in the Transformer experiments, the lemma-tag system achieves better results in BLEU for all settings.

6 Discussion of the linguistic impact and examples: BPE splitting vs. morphologically informed modeling

The experiments in the previous section showed that both the lemma-tag strategy and the segmentation strategy can improve the translation quality, even though the impact decreases with larger training data, in particular when looking at translating news data as opposed to special domains such as medical data. In this section, we try to get some insight into the effects on the linguistic level, in particular the effects of BPE splitting in contrast to the linguistically informed approaches, and compare the data representation of the different strategies.

BPE (Sennrich et al., 2016) is a common technique to reduce the vocabulary size in NMT. It relies entirely on word and sub-word frequencies observed in the data to split and thus does not require any external resources. However, the fact that it is not linguistically guided leads to sub-optimal splitting.
Table 10. Representation of inflection variants of the verb “schweigen” (to remain silent) in the training data of the large baseline system. Inflectional suffixes are highlighted in the first column.

| Word     | Freq | BPE     | Comment                        |
|----------|------|---------|--------------------------------|
| schweigen| 763  | schweigen| infinitive, present 3rd person plural |
| schweigt | 78   | schwei@@gt| present 3rd person singular    |
| schweige  | 1    | schwei@@ge| conjunctive 3rd person singular |
| schwiegen | 9    | sch@@wiehen| past 3rd person plural       |
| schwiegØ | 8    | sch@@wie@@g| past 3rd person singular      |
| geschwiegen | 55  | gesch@@wiegen| past participle                |

Table 11. Representation of inflection variants of the noun “Straftatbestand” (criminal offence) in the training data of the large baseline system. Inflectional suffixes are highlighted in the first column.

| Word          | Freq | BPE              | Comment          |
|---------------|------|------------------|------------------|
| Straftatbeständen | 16   | Straft@@at@@beständen | plural, dat     |
| Straftatbestände   | 40   | Straft@@at@@bestände   | plural, acc/nom/gen |
| StraftatbestandØ  | 64   | Straft@@at@@bestandØ  | singular, acc/nom/dat |
| Straftatbestands  | 6    | Straft@@at@@bestands  | singular, gen |

The example in Table 10 lists inflectional variants of the verb *schweigen* (to remain silent) which illustrate several problems that arise when using BPE on surface data:

- Non-concatenative processes, such as the shift from *ei* in present tense to *ie* in past tense, cannot be captured. Such changes of vowels in the stem are common in many German verbs and nouns.
- Inconsistent splitting of inflectional suffixes (here, there is no splitting in the infinitive form, but an approximative splitting of inflectional suffixes in two of the present tense forms (*schweigt*, *schweige*)).
- Different splitting for past tense forms, where the suffix *-en* remains attached, but the stem is split in the middle. The resulting segment *sch@@* is rather meaningless and, being a frequent German n-gram, can be found in many different contexts. Even worse, the part *wiegen* is another, unrelated word (*wiegen* = to weigh) which can lead to confusion with actual occurrences of *wiegen* during training.

It becomes clear from looking at the different forms that they are not represented efficiently by BPE. In the lemma-tag approach, the lemma is simply represented as *schweigen*<\textcolor{blue}{V}> in all instances, accompanied by the respective morphological tag.

Similar problems are shown in Table 11 for inflectional variants of the com-
plex noun *Straftatbestand* (*criminal offence*). Again, the inflectional suffixes are not handled in a consistent way. Furthermore, the first part of the compound is split unintuitively into *Straft*+*at*, rather than into *Straft*+*tat* (*punishable*+*deed*). In the lemma-tag system, the lemma is represented as *strafen*+*Tatbestand* after BPE splitting.

The reduction of surface forms by replacing inflected forms with lemma-tag pairs leads to a considerable decrease in surface forms, which provides a better basis for BPE splitting. Similarly, the segmentation strategy results in a linguistically sound and overall consistent segmentation, such that the subsequent BPE step will find compounds and inflectional suffixes already split.

Table 12 contrasts the vocabulary sizes in the respective settings and system variants. While the lemma-tag strategy already reduces the vocabulary size, the segmentation strategy leads to a considerable further reduction, presumably due to the explicit compound splitting prior to BPE.

### Table 12. Comparison of German vocabulary size for the different corpus settings.

| Corpus   | Baseline | LemmaTag | Segmentation |
|----------|----------|----------|--------------|
| Small    | 159,908  | 117,386  | 57,715       |
| Medium   | 300,224  | 227,292  | 92,433       |
| Large    | 401,256  | 306,190  | 113,966      |

7 Translation examples

In this section, some example translations are shown and discussed, in particular with regard to the creation of new words. The last example serves as basis to discuss the impact of the linguistic approaches on the morphological level.

#### 7.1 Creation of new words

The creation of new words based on linguistically sound parts (segmentation strategy) or by means of word generation (lemma-tag strategy) is an important factor in these translation approaches. In the following, we discuss two examples containing words not seen in the training data.

Table 13 shows an example for the creation of a new word as a translation for *church tower*: *Kirchturms* in the lemma-tag system, and *Kirchenturms* in the baseline output. The variant *Kirchturms* in the lemma-tag system is correct (cf. reference translation); the variant in the baseline is understandable, but the realization of the transitional element is incorrect. The segmentation system is making the same mistake. While there are instances of *Kirchturm* and *Kirchtürme* (plural) in the training

---

10 The splitting into *strafen*+*Tatbestand* vs. *Straftat*+*Bestand* is questionable, but it is consistent over all forms.
Table 13. Example: outputs of the baseline Transformer system (B) in comparison to the lemma-tag (LT) and segmentation (S) Transformer systems.

| B                      | Neben den Resten der Festung und des **Kirchturms** … |
|------------------------|-------------------------------------------------------|
| LT                     | Neben den Überresten der Festung und des **Kirchturms** … |
| S                      | Neben den Überresten der Festung und des **Kirchturms** … |
| REF                    | Neben den Überresten der Festung und des **Kirchturms** … |
| SRC                    | Besides the remains of the fortress and the **church tower** … |

data, the genitive form **Kirchturms** is unseen. For the lemma-tag version, it is rather straightforward to generate the respective form.

The example in Table 14 contrasts a sentence pair from the medical domain where the lemma-tag output contains the newly created word **patientenrelevanten** (**patient-relevant**), generated from the tag-lemma pair `<+ADJ><NoGend><Gen><P1><Wk> Patient<NN>@@ relevant<Pos>`, with @@ marking a BPE segmentation point. In contrast, the baseline produced the non-existing form **patientenwichtigen**, obtained from the BPE segments pati@@ ent@@ en@@ wichtigen – while this word creation can be easily understood, it is not the correct term in this context. We cannot definitely say why the the lemma-tag system generated the correct term, given that there is no instance of **patientenrelevant** at all in the training data. However, one possibility might be that the lemma-tag system learned that the structure *Word* + “relevant” more frequently leads to a valid adjective than **wichtig** (**important**) - hence, the more structured representation could have enabled indirectly the generation of the correct form. The different aspects and possibilities of word formation in the lemma-tag system are very interesting, and we plan on studying this task in future work.

The system with linguistically informed target word segmentation receives the hyphen-split input word **patient @-@ important** from its pre-processing and, in this context, translates it to the output token sequence `#L Patient @en@@ relevant $8$en`, which is assembled to the valid German word **patientenrelevanten** in post-processing.

When comparing the translation outputs with the reference translation, it becomes clear that the improvement in the lemma-tag system and the segmentation system is not reflected in the BLEU score, as the sentence is phrased differently in the reference translation. This is a common problem with BLEU (and most other automatic metrics) as they rely on matches in a reference translation.
Table 14. Example for creating a new word: outputs of the baseline system (B) in comparison to the lemma-tag system (LT) and the segmentation system (S).

|   | B                 | LT                  | S                  | REF                     | SRC                        |
|---|------------------|---------------------|--------------------|-------------------------|---------------------------|
|   | um Verbesserungen an **patientenwichtig**en klinischen Ergebnissen zu erkennen | to recognize improvements in “patient-important” clinical outcomes |                       |                          | to detect improvements in **patient-important** clinical outcomes |

Table 15. Example: outputs of the baseline Nematus system (B) in comparison to the lemma-tag (LT) and segmentation (S) Nematus systems.

|   | B                | LT                  | S                  | REF                        | SRC                        |
|---|------------------|---------------------|--------------------|---------------------------|---------------------------|
|   | Dieser Wertpapierkonto wurde im Namen der beiden Angeklagten geführt, und laut einer Erklärung des Clubs war seine Existenz dem Club nicht bekannt. | Dieses Wertpapierkonto wurde im Namen der beiden Angeklagten geführt, und laut einer Erklärung des Clubs war seine Existenz dem Club nicht bekannt. | Diese Wertpapierkonten wurden im Namen der beiden Angeklagten geführt, und laut einer Erklärung des Clubs war ihre Existenz dem Club unbekannt. | Dieses Wertpapierkonto lief auf den Namen des zweiten Angeklagten und war laut dessen Aussage dem Verein nicht bekannt. | This securities account was run in the name of the two defendants and according to a statement by the club its existence was not known to the club. |

### 7.2 Looking at the morphological level

When comparing the outputs of the different systems, it is difficult to find systematic differences. Obvious errors on the morphological level such as wrong agreement are rare, but they do exist, as can be seen in the example in Table 15: the translations are identical and correct, except for the inflection of **dieser** (this) in the baseline output. Even though the following word, **Wertpapierkonto** (securities account, literally securities paper account) does not exist in
the training data, it has been produced by both systems. In the lemma-tag system, the generation step has been straightforward: the word is composed through a BPE operation (marked by @@) from two meaningful units (plus the morphological tag), $<$+NN$>$<Neut><Nom><Sg><NA> Wertpapier$<$NN$>$@@ Konto. In the post-processing step, the inflected word as well as the accompanying demonstrative can be generated based on the respective morphological tags.

In the baseline system, the word is built from the more complicated (and non-meaningful) sequence Wertpapier@@ kon@@ to. While the form Wertpapierkonto itself is correct, the baseline failed to generate the correct article (dieser instead of dieses). The segmentation system has incorrectly formed a plural corresponding to the English accounts, instead of the correct singular corresponding to account.

While it is difficult to give a definite explanation, it is possible that the structure of the subsequent noun plays a role. Since the morphological features of a compound are determined by its head noun, in this case konto (account), the baseline has struggled here as the word got segmented through BPE. Such unfortunate splittings might be less problematic in simpler contexts (e.g. dieses Kon@ to: this account), but the addition of a modifier between head and article increases the difficulty for the system.

The example above, as well as the example in table 14, aim at illustrating that improvements with the lemma-tag and segmentation strategies are obtained rather indirectly, and are difficult to capture and explain. We assume that the reduction of word forms and the more consistent representation, in combination with the morphologically annotated tags, play an important role in generating correct word forms given the context, and consequently in the overall performance of the system.

### 7.3 Handling out-of-domain data

Table 16 shows translations obtained with the baseline and lemma-tag Nematus systems, as well as the transformer segmentation system. In this example, the lemma-tag system managed to produce an acceptable translation for ultrasound treatment, whereas the other systems translated sound as reasonable or healthy. Furthermore, the translation of the second part of the sentence makes it possible for a reader to guess the intended meaning, while the baseline translation contains unrelated words (skin colour instead of skin, and lecture instead of fracture). Similarly, the translation Bruchstätte (rupture place) in the segmentation system is semantically closer to fracture than the baseline translation, and thus better to understand.

### 8 Other language pair: English–Czech

To verify that the two strategies also work for another language pair, we re-implemented them to translate from English into Czech, which has a very rich morphology with regard to case. Huck et al. (2017) have previously highlighted how inflection often leads to out-of-vocabulary problems in English–Czech and have proposed a solution for phrase-based statistical machine translation.
Table 16. Example: outputs of the baseline Nematus system (B) vs. the lemma-tag Nematus system (LT) vs. the segmentation Transformer system (S), all trained on the large corpus, for a sentence from the HimL test set.

|   |   |
|---|---|
| **B** | In der Regel bedeutet die ultragesunde Behandlung, dass ein spezielles Gerät, das mit der Hautfarbe in Berührung kommt, täglich rund 20 Minuten lang an der Vorlesung liegt.  
*typically, the ultra-healthy treatment means that a special device that touches the skin colour abuts the lecture daily for roughly 20 minutes* |
| **LT** | In der Regel geht es bei der ultrasonden-Behandlung darum, ein spezielles Gerät mit der Haut in Kontakt zu bringen, das die Fraktur für etwa 20 Minuten täglich überzieht.  
*typically, the ultrasound treatment means to bring a special device in contact with the skin, that covers the fracture for around 20 minutes daily* |
| **S** | Normalerweise besteht eine ultravernünftige Behandlung darin, täglich etwa 20 Minuten lang eine Sondervorrichtung in Kontakt mit der Haut zu stellen, die die Bruchstätte überschwemmt.  
*usually, an ultra-reasonable treatment consists in putting for around 20 minutes daily a gadget in contact with the skin, which swamps the rupture place* |
| **REF** | In der Regel umfasst die Ultraschallbehandlung die Unterbringung einer besonderen Vorrichtung in den Kontakt mit der Haut über der Frakturstelle für etwa 20 Minuten täglich. |
| **SRC** | Typically, ultrasound treatment involves placing a special device in contact with the skin overlying the fracture site for around 20 minutes on a daily basis. |

**Data and setup.** For this experiment, we used a small and a medium training corpus, with data from the WMT translation shared task. The small training corpus (203,570 parallel sentences) is obtained from the news-commentary corpus, the medium training corpus is a concatenation of news-commentary, common-crawl and Europarl, resulting in 936,046 parallel sentences. As development and test sets, we used newstest2015 and newstest2016. We applied the same general pre-processing steps (tokenization, true-casing and filtering for length) as in the English–German setup. Furthermore, the hyperparameter settings for the translation experiments with the Transformer model are the same.

**Data pre-processing: Lemma-tag strategy.** The lemma-tag strategy for translating into Czech relies on the output of the morphological tagger Morphodita (Strakova et al., 2014). In a first step, the data is tagged and lemmatized. Then, the surface forms in the training data for the lemma-tag system are replaced by the respective pair of lemma and morphological tag. To generate inflected forms for the translation output, Morphodita is given the lemma-tag pair and outputs
Table 17. Results with Transformer for the English–Czech LemmaTag and Segmentation approaches in comparison to a system trained on surface forms (Baseline) in case-sensitive BLEU. Significant improvements over the baseline (p-value=0.05) are marked with *.

| English–Czech In-domain Translation | Small | Medium |
|-----------------------------------|-------|--------|
| Transformer BPE Baseline          | 10.9  | 20.1   |
| Transformer LemmaTag              | 14.5 *| 20.4   |
| Transformer Segmentation (light)  | 13.1 *| 20.4   |
| Transformer Segmentation (aggressive) | 13.2 *| 20.0   |

an inflected form. In some instances, Morphodita generates several forms for one lemma-tag pair. If this is the case, a word frequency list is used to select the most frequent form, in order to reflect preferences for e.g. orthographic variations.

In contrast to the English–German system, the English–Czech system is much simpler as it relies on only one analysis tool (Morphodita) instead of combining the output of two tools (the parser BitPar and the morphological resource SMOR).

The English–Czech system also shows that, given an adequate analysis tool, an implementation for another language pair is rather straightforward.

Data pre-processing: Segmentation strategy. Linguistically informed word segmentation of Czech follows the very same basic idea as previously adopted for German (Section 4.1), but for Czech we omit the compound splitter component. We cascade a Czech stemmer-based suffix splitter with BPE segmentation applied on top of the suffix-split data. An out-of-the-box Python implementation\cite{Dolamic2009} of the Czech stemming approach by Dolamic and Savov\cite{Dolamic2009} is modified for our purposes, i.e., we alter the stemmer’s code to not remove morphological suffixes but rather detach them from the stem and write them out as separate tokens. In order for the stemmer to purely act as a segmenter, we furthermore deactivate its integrated functionality for palatalization of stems. We evaluate both a light variant and an aggressive variant of linguistic suffix splitting with the Czech stemmer. The light variant is limited to treating Czech case and possessive. The aggressive variant deals with case, possessive, comparative, diminutive, augmentative, and derivational suffixes.

Results and discussion. Table\cite{Dolamic2009} shows the results for experiments with small and medium-sized training data. While the segmentation system and the lemma-tag system improve a lot when using only a small training corpus, there is considerably less improvement when using more training data. We assume that this is due to Czech’s morphological richness that is not nearly sufficiently represented in the

\footnote{http://research.variancia.com/czech_stemmer/}
baseline system in the small setting, which leads to the lemma-tag representation and the segmentation strategy having a significant impact here.

9 Related work

The modeling of morphology in machine translation has been presented and analyzed in many variants and settings, both for SMT and NMT scenarios.

For the generation of target-side morphology, many SMT systems made use of the so-called 2-step approach, in which a translation system first translates into an intermediate representation of the target-side data, and then applies a prediction step. In this second step, a model separate from the translation system can predict either directly a surface form, e.g. Toutanova et al. (2008), or grammatical features to be used for the generation of surface forms, for example Bojar and Kos (2010) and Fraser et al. (2012). An alternative to the 2-step approach has been presented by Chahuneau et al. (2013) who integrated synthetic phrases into the phrase-table of a phrase-based SMT system.

For an NMT setting, Tamchyna et al. (2017) presented a strategy to generate inflected forms from pairs of lemmas and tags for the language pairs English–German and English–Czech; the lemma-tag strategy described in this work is based on their system setup. The lemma-tag strategy discussed in this work – and in Tamchyna et al. (2017) – is conceptually related to the two-step approach in that the translation system operates on an abstract intermediate representation followed by the generation of inflected forms. However, with the lemmas and full morphological tags being output as a sequence by the translation system, there is no separate prediction step required. The second step thus consists only of a deterministic mapping between pairs of lemmas and tags to the corresponding inflected form. Note that an interesting alternative idea to this is to use character decoding guided by morphological information (Passban et al., 2018).

The work of Nădejde et al. (2017) showed that interleaving words and CCG super tags in the training data on the source and target side improves the translation quality. While we do not use CCG tags in our annotation, the morphological tags still provide shallow syntactic information (though only on the target side), and might even have an effect that goes beyond local agreement.

In the research area of word segmentation, several alternatives to BPE (Sennrich et al., 2016) have been proposed. Google is using an in-house sub-word unit segmentation algorithm (Schuster and Nakajima, 2012) within their NMT systems (Wu et al., 2016) to split words into “wordpieces”. The Google wordpiece model relies on a language model component, which BPE does not. BPE has gained more widespread acceptance in MT research and is in common use. Ataman et al. (2017) and Ataman and Federico (2018) considered both supervised and unsupervised splitting of agglutinative morphemes in Turkish, where Turkish is the source language. Their setup addresses the issues arising from translating out of a morphologically rich language, whereas our work focuses on translating into a language with rich morphology. Furthermore, an important linguistic difference here is that
Turkish is an agglutinative language, while German has fusional inflection and very productive compounding and Czech has highly productive fusional inflection. Pinnis et al. (2017) studied more effective segmentation (e.g., by modifying the BPE algorithm) and Banerjee and Bhattacharyya (2018) combined linguistic segmentation with BPE.

Table 18 gives an overview of the gains in BLEU between the baseline and the respective best system for strategies to translate into morphologically complex languages, as discussed above. The systems referred to in this table use RNN/Nematus architectures, with gains for the language pair EN→DE lying between 0.47 and 0.7, which is in the same order of magnitude than our improvements for the RNN system variants, even though it has to be noted that our training data size is smaller.

A difficult question concerns a more in-depth evaluation of our systems’ ability to handle morphological generalization. Challenge sets are a crucial area of interest here. We were initially very interested in carrying out challenge set evaluation using the challenge sets of Sennrich (2017) and Burlot et al. (2018), which capture, e.g., agreement problems, and are very useful for evaluating BPE. However, it is not clear what the tag representation in lemma-tag should look like when using challenge sets. If we use the gold standard tags, then it is very easy for lemma-tag to choose the correct sentence, but if we use incorrect tags, then lemma-tag cannot possibly make the correct choice. In practice, the lemma-tag system does not output incoherent sequences of tags, so it is not clear that this type of evaluation captures useful facts about lemma-tag. This is unfortunate, because challenge set evaluation is a clean way of trying to capture morphological generalization in other contexts.

A test suite analysis focusing on the morphological competence of NMT system variants can be found in Amrhein and Sennrich (2021). They evaluate segmentation strategies on different types of morphological phenomena in a controlled, semi-synthetic setting. To assess how well NMT systems trained on different subword and character-level representations can handle various non-concatenative morphological phenomena such as reduplication or vowel harmony, they insert artificial morphemes to mimic these phenomena into an German–English translation setting. The unique morphemes in an otherwise standard data representation allow to isolate the respective morphological phenomena, and thus to derive which segmentation strategy is best-suited for a particular morphological problem. While the analysis in Amrhein and Sennrich (2021) has a different focus than our main evaluation interest – measuring the modeling of specific non-concatenative phenomena vs. capturing morphological generalization as in our work, the method of isolating particular phenomena is promising and we are interested in taking it further to evaluate a larger range of morphological issues.

10 Conclusion

In this paper we compared two linguistically informed approaches to dealing with target-side morphology. The knowledge-rich approach represents words as a combination of a lemma and a rich POS tag, which is a sufficient representation for
| Work                        | Modeling                          | System | Lang.     | BLEU gain |
|-----------------------------|-----------------------------------|--------|-----------|-----------|
| Passban et al. (2018)       | split target-side                 | RNN    | EN→DE     | 0.47      |
|                             | agglutinative morphology          |        | EN→RU     | 0.61      |
|                             | (character-level decoder)         |        | EN→TR     | 0.60      |
| Nădejde et al. (2017)       | target-side syntax (CCG)          | Nematus| DE→EN     | 1.0$^s$   |
|                             | source-/target-side syntax        |        | DE→EN     | 1.1$^s$   |
|                             | source-side syntax (CCG)          |        | EN→DE     | 0.7$^s$   |
|                             | source-side syntax (CCG)          |        | EN→RO     | 0.5$^s$   |
| Pinnis et al. (2017)        | morph. guided segmentation        | Nematus| EN→LV     | 0.46$^*$  |
|                             |                                   |        | EN→LV     | 0.71$^*$  |
| Banerjee and Bhatacharyya   | morph. guided segmentation        | Nematus| BN→HI     | 1.12      |
|                             |                                   |        | EN→HI     | 0.65      |
|                             |                                   |        | EN→BN     | 0.68      |
| LemmaTag                   | inflection generation             | Transf.| EN→DE     | -0.2$^*$  |
| Segmentation                | linguistic segmentation           | Transf.| EN→DE     | 0.0$^*$   |
| LemmaTag                   | inflection generation             | Transf.| EN→DE     | 0.7$^s$   |
| Segmentation                | linguistic segmentation            | Transf.| EN→DE     | 0.4$^s$   |
| LemmaTag                   | inflection generation             | Nematus| EN→DE     | 0.8$^*$   |
| Segmentation                | linguistic segmentation            | Nematus| EN→DE     | 0.3$^*$   |
| LemmaTag                   | inflection generation             | Nematus| EN→DE     | 0.6$^c$   |
| Segmentation                | linguistic segmentation            | Nematus| EN→DE     | 0.5$^c$   |

Table 18. Comparison of our system in terms of BLEU gains with other systems for dealing with target-side morphological richness. For the EN→DE experiments, Nădejde et al. (2017) and Passban et al. (2018) use ~4.5M training sentences, compared to our ~2M sentences. $^s$: single system $^E$: ensemble model; $^*$: news domain $^c$: other domain.

generating the final surface forms. The knowledge-poor approach uses a simple linguistic segmentation strategy based on the information in a stemmer.

Our experiments show that the Transformer does not benefit as much from these approaches as the previous shallow-RNN systems did when translating in-domain test sets. However, for the out-of-domain scenario, where linguistic generalization is more challenging, both approaches produced large gains.

The knowledge-rich approach depends strongly on the performance of statistical disambiguation to produce the lemma-tag representation of the training corpus, and also on the coverage of the inflectional resource for producing the final translation output. Improvements in these resources could result in better translation performance. But the requirement to have such resources is an important aspect of
this approach. If such resources are available for a particular language pair, then it is an interesting approach to try.

The knowledge-poor approach depends only on having the sort of information that stemmers typically have access to, with just a small amount of hand-engineering necessary. Improved stemmers may slightly improve results, but will probably not drastically change the translation performance. This approach (and related approaches with stronger modeling of derivational morphology) should be available for many morphologically rich languages, and should certainly be tried for many language pairs for which only BPE-based systems have been built so far.

In summary, our study has shown that in comparison with the almost-linguistic-knowledge-free approach of BPE, which only requires substring frequencies, we can achieve important linguistic generalization through the use of knowledge-rich and knowledge-poor approaches, and that this effect is particularly strong in the case of translating out-of-domain.

Remarks

This paper was originally accepted for publication in a journal special edition in early 2020. However, due to the special edition being canceled entirely, this paper has remained unpublished. After much consideration, we decided to publish this study on arXiv.

Since writing this paper, we extended the lemma-tag approach to model word formation with a particular focus on handling non-concatenative morphological processes (Weller-Di Marco and Fraser, 2020), where we show that linguistic segmentation combined with morpho-syntactic information on both the source and the target side leads to improvements.

Acknowledgment

This research publication was partially funded by LMU Munich’s Institutional Strategy LMUexcellent within the framework of the German Excellence Initiative. This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreement № 640550). This work was supported by the Dutch Organization for Scientific Research (NWO) VICI Grant nr. 277-89-002.

References

Aharoni, R. and Goldberg, Y. (2017). Towards String-To-Tree Neural Machine Translation. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 132–140, Vancouver, Canada. Association for Computational Linguistics.

Amrhein, C. and Sennrich, R. (2021). How suitable are subword segmentation strategies for translating non-concatenative morphology? In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 689–705, Punta Cana, Dominican Republic. Association for Computational Linguistics.
Ataman, D. and Federico, M. (2018). Compositional Representation of Morphologically-Rich Input for Neural Machine Translation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Short Paper), pages 305–311, Melbourne, Australia.

Ataman, D., Negri, M., Turchi, M., and Federico, M. (2017). Linguistically Motivated Vocabulary Reduction for Neural Machine Translation from Turkish to English. In Proceedings of EAMT 2017, pages 331–342, Prague, Czech Republic.

Bahdanau, D., Cho, K., and Bengio, Y. (2014). Neural Machine Translation by Jointly Learning to Align and Translate. arXiv e-prints, abs/1409.0473. Presented at ICLR 2015.

Banerjee, T. and Bhattacharyya, P. (2018). Meaningless yet meaningful: Morphology grounded subword-level NMT. In Proceedings of the Second Workshop on Subword/Character Level Models.

Bastings, J., Titov, I., Aziz, W., Marcheggiani, D., and Sima’an, K. (2017). Graph Convolutional Encoders for Syntax-aware Neural Machine Translation. In Proceedings of EMNLP 2017, pages 1957–1967, Copenhagen, Denmark.

Bentivogli, L., Bisazza, A., Cettolo, M., and Federico, M. (2016). Neural versus Phrase-Based Machine Translation Quality: a Case Study. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 257–267, Austin, Texas. Association for Computational Linguistics.

Bojar, O., Chatterjee, R., Federmann, C., Graham, Y., Haddow, B., Huck, M., Jimeno Yepes, A., Koehn, P., Logacheva, V., Monz, C., Negri, M., Névéol, A., Neves, M., Popel, M., Post, M., Rubino, R., Scarton, C., Specia, L., Turchi, M., Verspoor, K., and Zampieri, M. (2016). Findings of the 2016 Conference on Machine Translation. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, pages 131–198, Berlin, Germany. Association for Computational Linguistics.

Bojar, O., Chatterjee, R., Federmann, C., Haddow, B., Huck, M., Proto, M., Koehn, P., Logacheva, V., Monz, C., Negri, M., Névéol, A., Neves, M., Popel, M., Post, M., Rubino, R., Scarton, C., Specia, L., Turchi, M., Verspoor, K., and Zampieri, M. (2015). Findings of the 2015 Workshop on Statistical Machine Translation. In Proceedings of the Tenth Workshop on Statistical Machine Translation, pages 1–46, Lisbon, Portugal. Association for Computational Linguistics.

Bojar, O., Federmann, C., Fishel, M., Graham, Y., Haddow, B., Huck, M., Koehn, P., and Monz, C. (2018). Findings of the 2018 Conference on Machine Translation (WMT18). In Proceedings of the Third Conference on Machine Translation, Volume 2: Shared Task Papers, pages 272–307, Brussels, Belgium. Association for Computational Linguistics.

Bojar, O. and Kos, K. (2010). 2010 Failures in English-Czech Phrase-based MT. In Proceedings of the Joint Fifth Workshop on Statistical Machine Translation and MetricsMATR, WMT ’10, pages 60–66, Stroudsburg, PA, USA. Association for Computational Linguistics.

Burlot, F., García-Martínez, M., Barrault, L., Bougares, F., and Yvon, F. (2017). Word Representations in Factored Neural Machine Translation. In Proceedings of the Second Conference on Machine Translation, pages 20–31, Copenhagen, Denmark. Association for Computational Linguistics.
Burlot, F., Knyazeva, E., Lavergne, T., and Yvon, F. (2016). Two-Step MT: Predicting Target Morphology. In Proceedings of the International Workshop on Spoken Language Translation, IWSLT’16, Seattle, WA.

Burlot, F., Scherrer, Y., Ravishankar, V., Bojar, O., Gröðroos, S.-A., Koponen, M., Nieminen, T., and Yvon, F. (2018). The WMT’18 morphoeval test suites for English-Czech, English-German, English-Finnish and Turkish-English. In Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pages 546–560, Brussels, Belgium. Association for Computational Linguistics.

Chahuneau, V., Schlinger, E., Smith, N. A., and Dyer, C. (2013). Translating into Morphologically Rich Languages with Synthetic Phrases. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1677–1687, Seattle, Washington.

Conforti, C., Huck, M., and Fraser, A. (2018). Neural Morphological Tagging of Lemma Sequences for Machine Translation. In Proceedings of the 13th Conference of the Association for Machine Translation in the Americas (AMTA 2018), vol. 1: MT Research Track, pages 39–53, Boston, MA, USA.

Dolamic, L. and Savoy, J. (2009). Indexing and stemming approaches for the Czech language. Information Processing & Management, 45(6):714–720.

Eriguchi, A., Hashimoto, K., and Tsuruoka, Y. (2016). Tree-to-Sequence Attentional Neural Machine Translation. In Proceedings of ACL 2016, pages 823–833, Berlin, Germany.

Fraser, A., Weller, M., Cahill, A., and Cap, F. (2012). Modeling Inflection and Word-Formation in SMT. In Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics, pages 664–674, Avignon, France. Association for Computational Linguistics.

Gage, P. (1994). A New Algorithm for Data Compression. C Users J., 12(2):23–38.

García-Martínez, M., Barrault, L., and Bougares, F. (2017). Neural Machine Translation by Generating Multiple Linguistic Factors. In Camelin, N., Estève, Y., and Martín-Vide, C., editors, Statistical Language and Speech Processing, pages 21–31, Cham. Springer International Publishing.

Haddow, B., Birch, A., Bojar, O., Braune, F., Davenport, C., Fraser, A., Huck, M., Kašpar, M., Kovaříková, K., Pleh, J., Ramn, A., Ried, J., Sheary, J., Tanchyna, A., Variš, D., Weller, M., and Williams, P. (2017). HimL: Health in my Language. In Proceedings of the EAMT 2017 User Studies and Project/Product Descriptions, page 33, Prague, Czech Republic.

Hieber, F., Domhan, T., Denkowski, M., Vilar, D., Sokolov, A., Clifton, A., and Post, M. (2017). Sockeye: A toolkit for neural machine translation. arXiv preprint arXiv:1712.05690.

Huck, M., Braune, F., and Fraser, A. (2017a). LMU Munich’s Neural Machine Translation Systems for News Articles and Health Information Texts. In Proceedings of the Second Conference on Machine Translation, Volume 2: Shared Task Papers, pages 315–322, Copenhagen, Denmark. Association for Computational Linguistics.

Huck, M., Riess, S., and Fraser, A. (2017b). Target-side Word Segmentation Strate-
gies for Neural Machine Translation. In *Proceedings of the Second ACL Conference on Machine Translation (WMT)*, pages 56–67, Copenhagen, Denmark.

Huck, M., Stojanovski, D., Hangya, V., and Fraser, A. (2018). LMU Munich’s Neural Machine Translation Systems at WMT 2018. In *Proceedings of the Third Conference on Machine Translation, Volume 2: Shared Task Papers*, pages 659–665, Brussels, Belgium. Association for Computational Linguistics.

Huck, M., Tamchyna, A., Bojar, O., and Fraser, A. (2017c). Producing Unseen Morphological Variants in Statistical Machine Translation. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 369–375, Valencia, Spain. Association for Computational Linguistics.

Jimeno Yépes, A., Névéol, A., Neves, M., Verspoor, K., Bojar, O., Boyer, A., Grozea, C., Haddow, B., Kittner, M., Lichtblau, Y., Pecina, P., Roller, R., Rosa, R., Siu, A., Thomas, P., and Trescher, S. (2017). Findings of the WMT 2017 Biomedical Translation Shared Task. In *Proceedings of the Second Conference on Machine Translation*, pages 234–247, Copenhagen, Denmark. Association for Computational Linguistics.

Kingma, D. P. and Ba, J. (2015). Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.

Koehn, P., Hoang, H., Birch, A., Callison-Burch, C., Federico, M., Bertoldi, N., Cowan, B., Shen, W., Moran, C., Zens, R., Dyer, C., Bojar, O., Constantin, A., and Herbst, E. (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, Prague, Czech Republic. Association for Computational Linguistics.

Koehn, P. and Knight, K. (2003). Empirical Methods for Compound Splitting. In *Proceedings of the 10th Conference of the European Chapter of the Association for Computational Linguistics*, pages 187–194, Budapest, Hungary. Association for Computational Linguistics.

Nádejde, M., Reddy, S., Sennrich, R., Dwojak, T., Junczys-Dowmunt, M., Koehn, P., and Birch, A. (2017). Predicting target language CCG supertags improves neural machine translation. In *Proceedings of the Second Conference on Machine Translation*, pages 68–79, Copenhagen, Denmark. Association for Computational Linguistics.

Neves, M., Jimeno Yépes, A., Névéol, A., Grozea, C., Siu, A., Kittner, M., and Verspoor, K. (2018). Findings of the WMT 2018 Biomedical Translation Shared Task: Evaluation on Medline test sets. In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*, pages 324–339, Brussels, Belgium. Association for Computational Linguistics.

Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2002). Bleu: a Method for Automatic Evaluation of Machine Translation. In *Proceedings of 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Passban, P., Liu, Q., and Way, A. (2018). Improving Character-Based Decoding
Using Target-Side Morphological Information for Neural Machine Translation. 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 58–68, New Orleans, Louisiana. Association for Computational Linguistics.

Pinnis, M., Krišlauks, R., Dekste, D., and Miks, T. (2017). Neural Machine Translation for Morphologically Rich Languages with Improved Sub-word Units and Synthetic Data.

Porter, M. (1980). An algorithm for suffix stripping. Program: electronic library and information systems, 14(3):130–137.

Schmid, H. (2004). Efficient Parsing of Highly Ambiguous Context-Free Grammars with Bit Vectors. In Proceedings of the International Conference on Computational Linguistics, pages 162–168, Geneva, Switzerland.

Schmid, H., Fitschen, A., and Heid, U. (2004). SMOR: A German Computational Morphology Covering Derivation, Composition, and Inflection. In Proceedings of the 4th International Conference on Language Resources and Evaluation (LREC), pages 1263–1266, Lisbon, Portugal.

Schuster, M. and Nakajima, K. (2012). Japanese and Korean voice search. In 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5149–5152.

Sennrich, R. (2017). How Grammatical is Character-level Neural Machine Translation? Assessing MT Quality with Contrastive Translation Pairs? In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL), Short Papers, pages 376–382, Valencia, Spain.

Sennrich, R., Firat, O., Cho, K., Birch, A., Haddow, B., Hintscher, J., Junczys-Dowmunt, M., Läubli, S., Miceli Barone, A. V., Mokry, J., and Nadejde, M. (2017). Nematus: a toolkit for neural machine translation. In Proceedings of the Software Demonstrations of the 15th Conference of the European Chapter of the Association for Computational Linguistics, pages 65–68, Valencia, Spain. Association for Computational Linguistics.

Sennrich, R., Haddow, B., and Birch, A. (2016). Neural Machine Translation of Rare Words with Subword Units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016.

Straková, J., Straka, M., and Hajíč, J. (2014). Open-Source Tools for Morphology, Lemmatization, POS Tagging and Named Entity Recognition. In Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 13–18, Baltimore, Maryland. Association for Computational Linguistics.

Tamchyna, A., Weller-Di Marco, M., and Fraser, A. (2017). Modeling Target-Side Inflection in Neural Machine Translation. In Proceedings of the Second ACL Conference on Machine Translation (WMT), pages 32–42, Copenhagen, Denmark.

Toutanova, K., Suzuki, H., and Ruopp, A. (2008). Applying Morphology Generation Models to Machine Translation. In Proceedings of ACL-08: HLT, pages 514–522, Columbus, Ohio. Association for Computational Linguistics.
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 6000–6010.

Weissweiler, L. and Fraser, A. (2017). Developing a Stemmer for German Based on a Comparative Analysis of Publicly Available Stemmers. In *Proceedings of the German Society for Computational Linguistics and Language Technology (GSCL)*, Berlin, Germany.

Weller-Di Marco, M. and Fraser, A. (2020). Modeling word formation in English–German neural machine translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4227–4232, Online. Association for Computational Linguistics.

Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., Klingner, J., Shah, A., Johnson, M., Liu, X., Kaiser, L., Gouws, S., Kato, Y., Kudo, T., Kazawa, H., Stevens, K., Kurian, G., Patil, N., Wang, W., Young, C., Smith, J., Riesa, J., Rudnick, A., Vinyals, O., Corrado, G., Hughes, M., and Dean, J. (2016). Google’s neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144.