Augmenting Neural Machine Translation with Knowledge Graphs

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Abstract

While neural networks have been used extensively to make substantial progress in the machine translation task, they are known for being heavily dependent on the availability of large amounts of training data. Recent efforts have tried to alleviate the data sparsity problem by augmenting the training data using different strategies, such as back-translation. Along with the data scarcity, the out-of-vocabulary words, mostly entities and terminological expressions, pose a difficult challenge to Neural Machine Translation systems. In this paper, we hypothesize that knowledge graphs enhance the semantic feature extraction of neural models, thus optimizing the translation of entities and terminological expressions in texts and consequently leading to a better translation quality. We hence investigate two different strategies for incorporating knowledge graphs into neural models without modifying the neural network architectures. We also examine the effectiveness of our augmentation method to recurrent and non-recurrent (self-attentional) neural architectures. Our knowledge graph augmented neural translation model, dubbed KG-NMT, achieves significant and consistent improvements of +3 BLEU, METEOR and chrF\textsuperscript{3} on average on the newstest datasets between 2014 and 2018 for WMT English-German translation task.

1 Introduction

Neural Network (NN) models have shown significant improvements in translation generation and have been widely adopted given their sustained improvements over the previous state-of-the-art Phrase-Based Statistical Machine Translation (PBSMT) approaches (Koehn et al., 2007). A number of NN architectures have therefore been proposed in the recent past, ranging from recurrent (Bahdanau et al., 2014; Sutskever et al., 2014) to self-attentional networks (Vaswani et al., 2017). However, a major drawback of Neural Machine Translation (NMT) models is that they need large amounts of training data to return adequate results and have a limited vocabulary size due to their computational complexity (Luong and Manning, 2016). The data sparsity problem in Machine Translation (MT), which is mostly caused by a lack of training data, manifests itself in particular in the poor translation of rare and out-of-vocabulary (OOV) words, e.g., entities or terminological expressions rarely or never seen in the training phase. Previous work has attempted to deal with the data sparsity problem by introducing character-based models (Luong and Manning, 2016) or Byte Pair Encoding (BPE) algorithms (Sennrich et al., 2016b). Additionally, different strategies were devised for overcoming the lack of training data, such as back-translation (Sennrich et al., 2016a).

Despite the significant advancement of previous work in NMT, translating entities and terminological expressions remains a challenge (Koehn and Knowles, 2017). Entities may be subsumed in two groups, i.e., proper nouns and common nouns. Proper nouns are also known as Named Entity (NE) and correspond to the name of persons, organizations or locations, e.g., \textit{Canada}. Common nouns describe classes of object, e.g., \textit{spoon} or \textit{cancer}. Both types of entities are found in a Knowledge Graph (KG), in which they are described within triples (Auer et al., 2007; Vrandečić and Krötzsch, 2014). Each triple consists of a subject—often an entity—, a relation—often called property—and an object—often an entity or a literal, e.g., a string or a value with a unit—. For example, \texttt{<NAACL, areaServed, North_America>} means in natural language that “\textit{NAACL takes place in North America}”\textsuperscript{1}. Re-

\textsuperscript{1}http://dbpedia.org/resource/NAACL
\textsuperscript{2}In this paper, we use KG and KB interchangeably.
cent work has exploited the contribution of KGs to improve distinct Natural Language Processing (NLP) tasks such as Natural Language Inference (NLI) (Annervaz et al., 2018), Question Answering (QA) (Sorokin and Gurevych, 2018; Sun et al., 2018) and Machine Reading (MR) (Yang and Mitchell, 2017) successfully. Additionally, the benefits of incorporating type information on entities—e.g., NE-tags such as PERSON, LOCATION or ORGANIZATION—into NMT by relying on Named Entity Recognition (NER) systems have been shown in previous works (Ugawa et al., 2018; Li et al., 2018). However, none of these have exploited the combination of Entity Linking (EL) with KGs in NMT systems.

The goal of EL is to disambiguate and link a given NE contained in a text to a corresponding entity—also called a resource—in a reference Knowledge Base (KB) (Moussallem et al., 2017). If the reference KB is bilingual, then the links generated by EL can be used to retrieve the translation of entities found in the text. In this work, we aim to use EL to improve the results of NMT approaches. We build upon recent works, which have devised Knowledge Graph Embeddings (KGE) approaches (Bordes et al., 2013), i.e., approaches that embed KGs into continuous vector spaces. Since neural models learn translations in a continuous vector space, we hypothesize that a given KG, once converted to embeddings, can be used along with EL to improve NMT models. Our results suggest that with this proposed methodology, we are capable of enhancing the semantic feature extraction of neural models for gathering the correct translation of entities and consequently improving the translation quality of the text.

We devised two strategies to implement the insight stated above. In our first strategy, we began by annotating bilingual training data with a multilingual EL system using a reference KB. Then, we map the entities and relationships contained in the reference KB to a continuous vector space using a KGE technique. Afterwards, we concatenate the KGE to the internal NMT embeddings, thus augmenting the embedding layer of NMT training. Given that EL can be time-consuming when faced with large training corpora, we skip the EL task in our second strategy and we semantically enrich the KGE by using the referring expressions of entities, also known as labels to initialize the vector values at the embedding layer. Differently from Venugopalan et al. (2016), we maximize the vector values of entities found in the bilingual corpora with the values of entities’ labels from the KGE. We perform an extensive automatic and manual evaluation in order to analyze our hypothesis. Among others, we examine the effectiveness of our augmentation method when combined with recurrent and non-recurrent (self-attentional) neural architectures, dubbed RNN and Transformer respectively. Our KG-augmented neural translation model, named KG-NMT, achieves significant and consistent improvements of +3 BLEU, METEOR and CHRF3 on average on the WMT newstest datasets between 2014 and 2018 for the English-German translation task, using a small set of two million parallel sentences. To the best of our knowledge, no previous work has investigated the augmentation of NMT by using KGs without affecting the NN architecture. Hence, the main contribution of this paper lies in the investigation of two different strategies for integrating KGE into neural translation models to maximize the probability score of the translation of entities. Moreover, we show that we can enhance the translation quality of NMT systems by incorporating KGE into the training phase.\footnote{Our data and models will be made publicly available.}

2 Related Work

NMT Augmentation. Different methods have been suggested to overcome the limitations of NMT vocabulary size. Luong and Manning (2016) implemented a hybrid solution, which combines word and character models in order to achieve an open vocabulary NMT system. Similarly, Sennrich et al. (2016b) introduced BPE, which is a form of data compression that iteratively replaces the most frequent pair of bytes in a sequence with a single, unused byte. Additionally, the use of monolingual data for data augmentation has gained considerable attention as it is not supposed to alter the NN architecture while demonstrating consistent results. Sennrich et al. (2016a) explored two methods using monolingual data during the training of an NMT system. They used dummy source sentences and relied on an automatic back-translation of the monolingual data using different NMT systems. Moreover, past work exploited the use of monolingual data to augment NMT systems in distinct NN architectures. Hoang et al. (2018) presented an iterative back-translation method, which generates increasingly synthetic parallel data from monolingual data while training.
a given NMT system. Also, Edunov et al. (2018) attempted to understand the effectiveness of back-translation in a large scale scenario by using different strategies on hundreds of millions of monolingual sentences. Recently, approaches other than back-translation for data augmentation were introduced. For example, Wang et al. (2018) proposed a method of randomly replacing words in both the source sentence and the target sentence with other random words from their corresponding vocabularies.

**External Structured Knowledge in MT.** According to a recent survey (Moussallem et al., 2018), the idea of using a structured KB in MT systems started with the work of Knight and Luk (1994). Still, only a few researchers have designed different strategies for benefiting of structured knowledge in MT architectures (McCrae and Cimiano, 2013; Arcan et al., 2015; Simov et al., 2016). Recently, the idea of using KG into MT systems has gained renewed attention. Du et al. (2016) created an approach to address the problem of OOV words by using BabelNet (Navigli and Ponzetto, 2012). Their approach applies different methods of using BabelNet. In sum, they create additional training data and also apply a post-editing technique which replaces the OOV words while querying BabelNet. Shi et al. (2016) have recently built a semantic embedding model reliant upon a specific KB to be used in NMT systems. The model relies on semantic embeddings to encode the key information contained in words so as to translate the meaning of sentences correctly.

**Named Entities in NMT.** Only a few works have investigated the NE translation issue in NMT. Some researchers worked on models specific to this problem, while others incorporated external information as features within NMT models. Li et al. (2016) and Wang et al. (2017b) rely on an NER tool to identify and align the NE pairs within the source and target sentences. Afterwards, the NE pairs are replaced with their corresponding NE-tags to train the model. In the translation phase, the targeted NE tags are then substituted with the original entities by a separate NE translation model or a bilingual NE dictionary. Ugawa et al. (2018) used a similar architecture but included one more layer in the encoder to encode the NE-tags expressed as chunk tags at each time step. The disadvantages of the methods above include NE information loss and NE alignment errors. To overcome these problems, Li et al. (2018) relied on an effective and simple method which added the NE-tags as boundary information to the entities directly inserted by an NER tool in the source sentence. It does not require either any separate model or external resource, and it therefore does not affect the NN architecture while achieving good performance.

**Knowledge Graph Embeddings.** According to Annervaz et al. (2018), we classify KGE into two categories: (1) Structure-based, which encodes only entities and relations, (2) Semantically-enriched, which takes into account semantic information of entities, e.g., text, along with the entities and its relations. (1) According to Wang et al. (2017a) manifold approaches, where relationships are interpreted as displacements operating on the low-dimensional embeddings of the entities, have been implemented so far, such as TransE (Bordes et al., 2013) and TransG (Xiao et al., 2015). However, Joulin et al. (2017b) showed recently that a simple Bag-of-Words (BoW) based approach with the fastText algorithm (Joulin et al., 2017a) generates surprisingly good KGE while achieving the state-of-the-art results. (2) Wang et al. (2014) proposed a technique of learning to embed structured and unstructured data (such as text) jointly in an effort to augment the prediction models. Additionally, Zhong et al. (2015) introduced an alignment of entities and word embeddings considering the description of entities. More work on agglutinating the semantics with entities arose, such as SSP (Xiao et al., 2017) and DKRL (Xie et al., 2016a) as well as TKRL (Xie et al., 2016b).

### 3 The KG-NMT Methodology

KG-NMT is based on the observation that more than 150 billion facts referring to more than 3 billion entities are available in the form of KG on the Web (McCrae et al., 2018). Hence, the intuition behind our methodology is as follows: *Given that KGs describe real-world entities, we can use KGs along with EL to optimize the entries in the vector of entities and consequently to achieve a better translation quality of entities in text.* In the following, we give an overview of NMT and KGE. Afterwards, we present how we use EL and KGE to augment NMT models. Throughout the description of our methodology and our experiments, we used DBpedia (Auer et al., 2007) as reference KB.
3.1 Background

3.1.1 Neural Machine Translation

We use two different NMT architectures, the Recurrent Neural Network (RNN) and Transformer-based models. Both consist of an encoder and a decoder, i.e., a two-tier architecture where the encoder reads an input sequence \( x = (x_1, ..., x_n) \) and the decoder predicts a target sequence \( y = (y_1, ..., y_n) \). The encoder and decoder interact via a soft-attention mechanism (Bahdanau et al., 2014; Luong et al., 2015), which comprises of one or multiple attention layers. We follow the notations from Tang et al. (2018b) in the subsequent sections: \( h_i^l \) corresponds to the hidden state at step \( i \) of layer \( l \). \( h_{l-1}^i \) represents the hidden state at the previous step of layer \( l \) while \( h_{l-1}^{i-1} \) means the hidden state at \( i \) of \( l-1 \) layer. \( E \in \mathbb{R}^{n \times m} \), \( W \in \mathbb{R}^{n \times m} \) and \( U \in \mathbb{R}^{n \times m} \) are weight matrices, with \( m \) being the word embedding size and \( n \) the number of hidden units. \( K_x \) is the vocabulary size of the source language. Thus, \( E_{x_i} \) refers to the embedding of \( x_i \), and \( e_{pos,i} \) indicates the positional embedding at position \( i \).

**RNN-based NMT.** In RNN models, networks change as new inputs (previous hidden state and the token in the line) come in, and each state is directly connected to the previous state only. Therefore, the path length of any two tokens with a distance of \( n \) in RNNs is exactly \( n \). Its architecture enables adding more layers, whereby two adjoining layers are usually connected with residual connections in deeper configurations. Equation 1 displays \( h_i^l \), where \( f_{rn} \) is usually a function based on Gated recurrent unit (GRU) (Cho et al., 2014) or Long Short-Term Memories (LSTM) (Hochreiter and Schmidhuber, 1997). The first layer is then represented as \( h_{0}^{0} = f_{rn}(WE_{x_i}, Uh_{-1}^{0}) \). Additionally, the initial state of the decoder is commonly initialized with the average of the hidden states or the last hidden state of the encoder.

\[
h_i^l = h_{i-1}^{l-1} + f_{rn}(h_{i-1}^{l-1}, h_{i-1}^{l}) \tag{1}
\]

**Transformer-based NMT.** Transformer models rely deeply on self-attention networks. Each token is connected to any other token in the same sentence directly via self-attention. Thus, the path length between any two tokens is 1. Additionally, these models rely on multi-head attention to feature attention networks, which are more complex in comparison to 1-head attention mechanisms used in RNNs. In contrast to RNN, the positional information is also preserved in positional embeddings. Equation 2 represents the hidden state \( h_i^l \), which is calculated from all hidden states of the previous layer. \( f \) represents a feed-forward network with the rectified linear unit (ReLU) as the activation function and layer normalization. The first layer is represented as \( h_{0}^{0} = WE_{x_i} + e_{pos,i} \). Moreover, the decoder has a multi-head attention over the encoder hidden states.

\[
h_i^l = h_{i-1}^{l-1} + f(\text{self-attention}(h_{i-1}^{l-1})) \tag{2}
\]

3.1.2 Knowledge Graph Embeddings

The underlying concept of KGE is that, in a given KB, each subject \( h \) or object \( t \) entity can be associated as a point in a continuous vector space whereby its relation \( r \) can be modelled as displacement vectors \((h + r = t)\) while preserving the inherent structure of the KG. In the methodology introduced by Joulin et al. (2017b), named fastText, the model is based on BoW representation which considers the subject \( h \) and object \( t \) entities along with its relation \( r \) as a unique discrete token. Thus, fastText models the co-occurrences of entities and its relations with a linear classifier and standard cost functions. Hence, it allows theoretically creating either a Structure-based or Semantically-enriched KGE. Therefore, we use fastText models in our experiments, represented by the following equation Equation 3.

\[
-\frac{1}{N} \sum_{n=1}^{N} y_n \log(f(WVz_n)), \tag{3}
\]

The normalized BoW of the \( x_n \) input set is represented as \( z_n \), \( y_n \) as the label. \( V \) is a matrix, which is used as a look-up table over the discrete tokens and a matrix \( W \) is used for the classifier. The representations of the discrete tokens are averaged into BoW representation, which is in turn fed to the linear classifier. \( f \) is used to compute the probability distribution over the classes, and \( N \) input sets for discrete tokens. We denote the generated KGE as \( E' \).

3.2 Methodology

Recent work has successfully devised strategies for incorporating different kinds of knowledge into NMT models, such as linguistic features (Sennrich and Haddow, 2016) and NE-tags (Gu et al., 2016). Differently—but inspired by the above-mentioned approaches—instead of training
Entity Linking: Let \( \mathcal{E} \) be a set of entities from a KB and \( \mathcal{D} \) be a document containing potential mentions of entities \( m = (m_1, \ldots, m_n) \). The goal of an EL system is to generate an assignment \( \mathcal{F} \) of mentions to entities with \( \mathcal{F}(m) \in (\mathcal{E})^n \) for the document \( \mathcal{D} \).

**Definition 1** Entity Linking: Let \( \mathcal{E} \) be a set of entities from a KB and \( \mathcal{D} \) be a document containing potential mentions of entities \( m = (m_1, \ldots, m_n) \). The goal of an EL system is to generate an assignment \( \mathcal{F} \) of mentions to entities with \( \mathcal{F}(m) \in (\mathcal{E})^n \) for the document \( \mathcal{D} \).

**Definition 2** Knowledge Base: We define KB \( K \) as a directed graph \( G_K = (V, R) \) where the nodes \( V \) are resources of \( K \), the edges \( R \) are properties of \( K \) and \( h, t \in V, (h, t) \in R \). A triple is a triple in \( K \).

We devised two strategies to instantiate our methodology. In the first training strategy, we link the NEs in the source and target texts to a reference KB using a given multilingual EL system. We then incorporate the Uniform Resource Identifier (URI)s of entities along with the tokens akin to Li et al. (2018) with the NE-tags. For example, the word Kiwi can be annotated with dbr:Kiwi\(^5\) or dbr:Kiwi\(_{\text{people}}\), depending on the context. Similarly, the word cancer can be annotated with cancer\(_{\text{dbr:Cancer}}\)\(^6\) and its translation can be found in the German part of the DBpedia KB (dbr:Krebs\(_{\text{Medizin}}\)). After incorporating the URIs, we embed the reference KB, DBpedia, using the fastText KGE algorithm. Once the KGE embeddings are created, we concatenate their vectors to the internal vectors of NMT embeddings. The concatenation is possible as the annotations, i.e., URIs, are present in the texts and consequently in the vocabulary (Speer and Lowry-Duda, 2017). Formally, let the tokens from the source and target text be elements of a fixed vocabulary \( \mathcal{D} \) which are used to train a given NMT model, while the assignments \( \mathcal{F} \) are the nodes \( V \) within KB \( K \). The embeddings \( E' \) of \( K \) can be concatenated along with the internal embeddings of NMT \( E \) using a function \( \text{concat}(E, E') \), thus resulting in a new vector \( E' \). With this modification the first layer of an RNN becomes \( h_i^0 = f_{rnn}(WE_{cx}, Uh_{i-1}) \).

Although incorporating EL as a feature into NMT is interesting by itself, the annotation of entities in the training set and the post-editing can be resource-intensive. Additionally, one limitation of Structure-based KGEs is that it can only work with word-based models since it is not possible to apply any segmentation model on entities and relations, since segmentation may force the algorithm to assign wrong vectors to the entities. For example, the entities dbr:Leipzig and dbr:Leibniz can be similar when considering sub-word units, however, the first is a location while the second is a person. Thus, they should not be regarded as similar. To overcome both limitations, we devised our second strategy which uses only Semantically-enriched KGEs and skips the EL part. Here, we enrich the Structure-based KGE with referring expressions of the entities found in the KB, thus decreasing the annotation effort. To generate the Semantically-enriched KGE, we rely on a classifier in a supervised training implemented in fastText which assigns a label to a given entity. For example, we add to the triple, <NAACL, areaServed, USA> the following information, <NAACL, label, North American Chapter of the Association for Computational Linguistics>\(^7\). By enriching the KGE, it allows us to use the vectors to initialize the embedding layer’s weights of the NMT models similarly to Neishi et al. (2017), which used pre-trained monolingual embeddings. Furthermore, it also enables applying segmentation to the labels, which allows work with BPE models. Commonly, the initialization of the embeddings layer is a function which assigns random values to the weight matrix \( W \), whereas in our second strategy, the values from KGE \( E' \) matrix are used to assign constant values to matrix \( W \) using a function \( \text{init}(E') \).

### 4 Experimental Setup

In our experiments, we used the multilingual EL system introduced by Moussallem et al. (2017) which is language and KB agnostic. Also, it does not require any training and still has shown

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\(^4\)We assume that all mentions can be linked to entities in the KB.

\(^5\)http://dbpedia.org/resource/Kiwi

\(^6\)http://dbpedia.org/resource/Cancer

\(^7\)More than one label can be assigned to the entities.
competitive results according to the benchmarking platform GERBIL (Usbeck et al., 2015). Different NN architectures are complex to compare as they are susceptible to hyper-parameters. Therefore, the idea was to use a minimal reasonable configuration set in order to allow a fair analysis of the real KG contributions. For our overall experiments, the RNN-based models use a bi-directional 2-layer LSTM encoder-decoder model with attention (Bahdanau et al., 2014). The training uses a batch size of 32 and the stochastic gradient descent with an initial learning rate of 0.0002. We set a word embeddings’ size of 500, and hidden layers to size 500, dropout = 0.3 (naive). We use a maximum sentence length of 80, a vocabulary of 50 thousand words and a beam size of 5. All experiments were performed with OpenNMT (Klein et al., 2017). In addition, we encoded words using BPE (Sennrich et al., 2016b) with 32,000 merge operations to achieve an open vocabulary. OpenNMT enables substitution of OOV words with target words that have the highest attention weight according to their source words (Luong et al., 2015) and when the words are not found, it uses a copy mechanism which copies the source words to the position of the not-found target word (Gu et al., 2016). Thus, we used all the options mentioned above to evaluate the performance of the translation quality. We trained the KGEs with a vector dimension size of 500 with a window size of 50 by using 12 threads with hierarchical soft-max. In addition, to Semantically-enriched KGE we added the labels whereby we use sub-word units with values of 2 to the min and 5 to the max. To compare both KGE types, we dubbed the KG-NMT approach that relies on EL and Structured-based KGE as KG-NMT (EL+KGE). The version with semantic information is named KG-NMT (SemKGE). For training, we attempted to be as generic as possible. Thus, our training set consists of a merge of the initial one-third of JRC-Acquis 3.0 (Steinberger et al., 2006), Europarl (Koehn, 2005) and OpenSubtitles2013 (Tiedemann, 2012), obtaining a parallel training corpus of two million sentences, containing around 38M running words. We used the English and German versions of DBpedia as our reference KG. The English KB contains 4.2 million entities, 661 relations, and 2.1 million labels, while the German version has 1 million entities, 249 relations, and 0.5 million labels. As the measurement of translation quality is inherently subjective, we used three automatic MT metrics to ensure a consistent and clear evaluation. Besides BLEU (Papineni et al., 2002), we use METEOR (Banerjee and Lavie, 2005) and CHRF3 (Popović, 2017) on the newstest between 2014 and 2018 for testing the models. Moreover, we carried out a manual analysis of outputs for assuring the contribution from KGE and we investigated the use of KGE in other settings.

RNN vs Transformer. Previous work has compared NN architectures on a variety of NLP tasks (Yin et al., 2017; Linzen et al., 2016; Bernardy and Lappin, 2017). However, few investigated RNN and Transformer architectures on the translation task. Recently, Tran et al. (2018) concluded that RNN performs better than Transformer on a subject-verb agreement task, while Tang et al. (2018a) found that Transformer models surpass RNN models only in high-resource conditions. Lastly, Tang et al. (2018b) compared RNN and Transformers on subject-verb agreement and Word Sense Disambiguation (WSD) by scoring contrastive translation pairs. Their findings show that Transformer models overcome RNN at WSD task, showing that they are better at extracting semantic features. In this sense, we decided to perform a comparison between both architectures in
showing that segmentation on labels of KG-NMT on BPE also presented consistent improvements kind of entities present in the KG. The models performance which did not manage to annotate all for METEOR. This difference between the contri-
chrF3, while we observe a +2 point improvement by around +1.3 in BLEU and NMT (EL+KGE)
F3 (+3), METEOR (+4) and significantly improved the translation quality in terms of BLEU(+3), METEOR (+4) and chrF3 (+3) metrics. KG-NMT (SemKGE) outperformed KG-NMT (EL+KGE) by around +1.3 in BLEU and chrF3, while we observe a +2 point improvement for METEOR. This difference between the contribution of KGE types is directly related to the EL performance which did not manage to annotate all kinds of entities present in the KG. The models on BPE also presented consistent improvements showing that segmentation on labels of KG-NMT (SemKGE) model worked. Moreover, the use of the copy mechanism along with KGE got the best results as expected since some entities which were not found in KG, i.e., unfamous persons, were copied from their source words and correctly translated. For example, the entity Chad Johnston appeared in line 1487 of the newstest2015 dataset, but this name was not found in the KB as an entity even though translated correctly.

A detailed study of our results showed that the number of OOV words decreased considerably with the augmentation through KGE. Table 2 shows the number of OOV words generated by the RNN models across all WMT newstest datasets. The statistics cannot ensure that every OOV word that became a known word was essentially an entity presented in KG. Thus, we chose the newstest2015 for a manual analysis. First, we leveraged the METEOR scores to identify sentences with a large number of OOV words. We observed that many OOV words were in fact entities contained in the KG. As an example (line 1265), UK was not translated by RNN baseline even using the copy mechanism (UK) and BPE (Britische). However, it was correctly translated into German as Großbritannien by both KGE models. Similarly, the entity Coastguard (line 1540) was not translated correctly by baseline models, whereby both KGE models were able to translate it into Küstenwache. However, we observed translation mistakes regarding gender information in German. For example, while KG-NMT (EL+KGE) was able to translate the word principal (line 438) correctly into Direktor but using the feminine gender (die Direktorin). An interesting observation regarding the use of EL is that some entities which were not annotated in the source text, were correctly annotated with a German URI in the translated text. This human evalu-

| Models       | newstest2014 | newstest2015 | newstest2016 | newstest2017 | newstest2018 |
|--------------|--------------|--------------|--------------|--------------|--------------|
|              | Bleu Met chrF3 | Bleu Met chrF3 | Bleu Met chrF3 | BBleu Met chrF3 | Bleu Met chrF3 |
| Word         |              |              |              |              |              |
| RNN baseline | 14.47 33.52 40.03 | 16.77 35.1 41.11 | 18.55 36.62 42.54 | 15.1 33.75 39.52 | 20.53 39.02 43.92 |
| KG-NMT (EL+KGE) | 17.19 36.61 42.14 | 19.86 38.25 42.92 | 22.38 40.40 45.18 | 18.04 36.94 41.55 | 24.87 43.49 46.88 |
| KG-NMT (SemKGE) | 18.58 38.62 43.55 | 21.49 40.19 44.72 | 24.01 42.47 46.84 | 19.66 38.89 43.11 | 27.02 45.77 48.70 |
| CopyM        |              |              |              |              |              |
| RNN baseline | 16.75 37.16 44.93 | 19.63 39.20 46.38 | 21.37 40.90 47.85 | 17.88 37.89 44.85 | 24.22 43.96 50.15 |
| KG-NMT (EL+KGE) | 19.53 39.88 47.18 | 22.46 41.67 48.28 | 25.05 44.23 50.66 | 20.77 40.58 47.04 | 28.44 47.86 53.25 |
| KG-NMT (SemKGE) | 20.97 41.55 48.39 | 24.08 43.43 49.72 | 26.70 46.08 52.05 | 22.30 42.37 48.36 | 30.55 49.92 54.71 |
| BPE32 CopyM  |              |              |              |              |              |
| RNN baseline | 16.33 38.93 49.82 | 15.89 36.51 45.97 | 21.95 42.88 52.68 | 16.8 39.12 49.35 | 23.85 45.85 54.98 |
| KG-NMT (EL+KGE) | N/A N/A N/A | N/A N/A N/A | N/A N/A N/A | N/A N/A N/A | N/A N/A N/A |
| KG-NMT (SemKGE) | 19.03 39.82 49.64 | 21.74 41.41 50.04 | 24.86 44.32 52.59 | 20.45 40.62 49.45 | 28.02 47.51 55.16 |

Table 1: Results of RNN models in BLEU (Bleu), METEOR (Met), chrF3 on WMT newstest datasets. Word → word-based models, CopyM → Copy Mechanism and BPE32 → BPE models.

order to analyze our hypothesis with KGs. To build a Transformer-based KG-NMT model, we followed the specifications found at Vaswani et al. (2017), which use a 6-layer encoder-decoder, a batch size of 4076, 8 heads, word embeddings and hidden layers of size 512. The Adam optimizer with a learning rate of 2 and a dropout of 0.1 was used. We used the same values to sentence length, beam, and BPE.

Monolingual Embeddings vs. KGE. Here, we aim to compare the performance of an NMT using pre-trained monolingual embeddings with the Semantically-enriched KGE as both can be used to initialize the internal vectors’ values of an NMT model. Our focus is to analyze if the KGE with fewer words and vectors can perform better than the monolingual embeddings for addressing the translation of entities and terminologies. We used the pre-trained monolingual embeddings from Bojanowski et al. (2017) for English which has 9.2 billion words and the German from Grave et al. (2018) with 1.3 billion words.

5 Results

Overall results Table 1 depicts the results from KG-NMT using RNN architecture on the newstest dataset between 2014 and 2018. Using KGE leads to a clear improvement over the baseline as it significantly improved the translation quality in terms of BLEU(+3), METEOR (+4) and chrF3 (+3) metrics. KG-NMT (SemKGE) outperformed KG-NMT (EL+KGE) by around +1.3 in BLEU and chrF3, while we observe a +2 point improvement for METEOR. This difference between the contribution of KGE types is directly related to the EL performance which did not manage to annotate all kinds of entities present in the KG. The models on BPE also presented consistent improvements showing that segmentation on labels of KG-NMT (SemKGE) model worked. Moreover, the use of the copy mechanism along with KGE got the best results as expected since some entities which were not found in KG, i.e., unfamous persons, were copied from their source words and correctly translated. For example, the entity Chad Johnston appeared in line 1487 of the newstest2015 dataset, but this name was not found in the KB as an entity even though translated correctly.

A detailed study of our results showed that the number of OOV words decreased considerably with the augmentation through KGE. Table 2 shows the number of OOV words generated by the RNN models across all WMT newstest datasets. The statistics cannot ensure that every OOV word that became a known word was essentially an entity presented in KG. Thus, we chose the newstest2015 for a manual analysis. First, we leveraged the METEOR scores to identify sentences with a large number of OOV words. We observed that many OOV words were in fact entities contained in the KG. As an example (line 1265), UK was not translated by RNN baseline even using the copy mechanism (UK) and BPE (Britische). However, it was correctly translated into German as Großbritannien by both KGE models. Similarly, the entity Coastguard (line 1540) was not translated correctly by baseline models, whereby both KGE models were able to translate it into Küstenwache. However, we observed translation mistakes regarding gender information in German. For example, while KG-NMT (EL+KGE) was able to translate the word principal (line 438) correctly into Direktor but using the feminine gender (die Direktorin). An interesting observation regarding the use of EL is that some entities which were not annotated in the source text, were correctly annotated with a German URI in the translated text. This human evalu-


| Model                  | 2014 | 2015 | 2016 | 2017 | 2018 |
|------------------------|------|------|------|------|------|
| RNN baseline           | 16.75| 19.63| 21.37| 17.88| 24.22|
| Transformer baseline   | 19.88| 24.12| 27.70| 20.63| 27.70|
| RNN + EL + KGE         | 19.53| 20.16| 27.70| 20.63| 27.70|
| Transformer + EL + KGE | 18.79| 21.00| 26.43| 19.20| 26.43|
| RNN + SemKGE           | 21.95| 22.30| 28.42| 20.63| 28.44|
| Transformer + SemKGE   | 19.70| 22.61| 28.42| 20.05| 28.44|

Table 2: Statistics of OOV words with RNN on newstest between 2014 and 2018.

Monolingual Embeddings vs KGE. Table 4 reports no significant difference between monolingual embeddings and KGE in terms of BLEU, METEOR, and chrF3. At first glance, this finding is interesting since the monolingual embeddings contain billions of words, compared to the DBpedia KG with 4.2 million entities. However, our manual analysis showed that the OOV words addressed by the monolingual embeddings were not in fact entities, but common words and the entities remained unknown. As an example, the RNN + MonoE model translated incorrectly the entity Principal into Wichtigste, while the KG-NMT (SemKGE) used the knowledge documented in the KGs. Moreover, RNN + MonoE was not able to translate the entities UK and Coastguard. Therefore, we envisage that a combination of both is promising and may lead to better results.

6 Conclusion

In this paper, we introduced an augmentation methodology which relies on the use of KGS to improve the performance of NMT systems. We devised two strategies for incorporating KG embeddings into NMT models which works on word- and character-based models. Additionally, we carried out an extensive evaluation with a manual analysis which showed consistent enhancements provided by KGs in NMT. The overall methodology can be applied to any NMT model structure and also allows replacing different EL systems.

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8For the sake of space, we only display BLEU results, but we also measured METEOR and chrF3.
9Due space limitation, we only display 2017 and 2018.
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