

Machine Translation Using Semantic Web Technologies: A Survey

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Abstract

A large number of machine translation approaches have been developed recently with the aim of migrating content easily across languages. However, the literature suggests that many obstacles must be dealt with to achieve better automatic translations. A central issue that machine translation systems must handle is ambiguity. A promising way of overcoming this problem is using semantic web technologies. This article presents the results of a systematic review of approaches that rely on semantic web technologies within machine translation approaches for translating texts. Overall, our survey suggests that while semantic web technologies can enhance the quality of machine translation outputs for various problems, the combination of both is still in its infancy.

Keywords: machine translation, semantic web, ontology, linked data, multilinguality

1. Introduction

Alongside strengthening globalization comes an increasing need for the understanding of texts in languages not spoken by the reader. For example, approximately 45% of the pages on the Web are not available in English [1, 2]. The technological progress of recent decades has rendered both the distribution and access to content in different languages ever simpler. Translation aims to support users who need to access content in a language in which they are not fluent [3, 4].

However, translation is a difficult task due to the complexity of natural languages and their structure [5]. In addition, manual translation does not scale to the proportions of the Web. One remedy to this problem is Machine Translation (MT). The main goal of MT is to enable people to assess content in languages other than the languages in which they are fluent [6]. From a formal point of view, this means that the goal of MT is to transfer the semantics of text from an input language to an output language [7]. At the time of writing, large information portals such as Google¹ or Bing² already offer MT services that are widely used.

Although MT systems are now popular on the Web, they still generate a large number of incorrect translations. Recently, Popovic [8] has classified five types of errors which still remain

in MT systems. According to research, the two main faults that are responsible for 40% and 30% of problems respectively, are reordering errors and lexical and semantic ambiguity. Thus, addressing these barriers is a key challenge for modern translation systems.

A large number of MT approaches have been developed over the years and could potentially serve as a remedy. For instance, translators began by using methodologies based on linguistics which led to the family of Rule-Based Machine Translation (RBMT). However, RBMT systems have a critical drawback in their reliance on manually crafted rules, thus making the development of translation modules for previously unseen languages difficult [9, 10].

Statistical Machine Translation (SMT) and Example-Based Machine Translation (EBMT) were developed to deal with the scalability issue behind RBMT [11], a necessary characteristic of MT systems that must deal with data at Web scale. Presently, these approaches have begun to address the drawbacks of rule-based approaches. However, some problems that had been already solved for linguistics based methods reappeared. The majority of these problems are connected to the issue of ambiguity, including syntactic and semantic variations [4].

Subsequently, RBMT and SMT have been combined in order to resolve the drawbacks of these two families of approaches. This combination of methods is called hybrid MT. Although hybrid approaches have been achieving good results, they still suffer from some RBMT problems [12–14]. Nowadays, a novel SMT paradigm has arisen called Neural Machine Translation (NMT) which relies on Neural Network (NN) algorithms. NMT has been achieving impressive results and is now the state-of-

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¹<http://translate.google.com.br/about/>

²<http://www.bing.com/translator/help/>

the-art in MT approaches. However, NMT is still a statistical approach which shares some semantic drawbacks from other well-defined SMT approaches[15].

One possible solution to address the remaining issues of MT lies in the use of Semantic Web Technologies (SWT), which have emerged over recent decades as a paradigm to make the semantics of content explicit so that it can be used by machines [16]. It is believed that the explicit semantic knowledge made available through these technologies can empower MT systems to supply translations with significantly better quality while remaining scalable [17]. In particular, the disambiguated knowledge about real-world entities, their properties and their relationships made available on the Linked Data (LD) Web can potentially be used to infer the right meaning of ambiguous sentences or words and also to support the reordering task.

The obvious opportunity of using SWT for MT has already been studied by a number of approaches. This systematic survey gives an overview of existing systems which make use of such a combination and presents the difference in translation quality that they achieve, especially w.r.t. the issue of ambiguity. Based on this overview, we distill the challenges and opportunities in the use of SWT in MT for translating texts.

This paper is structured as follows: In Section 2, we describe the methodology used to conduct this systematic survey. Section 3 discusses different MT approaches and their particular challenges. Section 4 shows how SWT have been used in MT approaches and presents suggestions on how to handle the challenges. Section 5 concludes with ideas for future work.

2. Research Method

The research methodology behind this survey follows the formal systematic literature review process. In particular, this study is based on the guidelines proposed in [18–20]. As detailed below, we also took into account other surveys from relevant journals as well as surveys about related topics such as Word Sense Disambiguation (WSD) and Semantic Web (SW).

2.1. Research Questions

The goal of this survey is to provide SW researchers with existing methodologies that use SWT applied to MT systems for translating natural-language sentences. To achieve this goal, we aimed to answer the following general research question: *How can SWT enhance MT quality?* This question was then divided into four sub-questions as follows:

- RQ1. What are state-of-the-art approaches in MT which use SWT?
- RQ2. Which SWT are applied in MT?
- RQ3. Does ontological knowledge influence the quality of an automatic translation?
- RQ4. What kinds of SW driven tools are available for MT?

RQ1 intends to collect available research works which retrieve knowledge from SW resources for translating texts. **RQ2** aims to provide an explicit comparison among SWT used in each respective MT approach. **RQ3** attempts to resolve whether inclusion of a certain concept represented or inferred by an ontology supports and improves the translation process of a given MT system. **RQ4** asks for a description of all available SW tools which have been used and may be used in future work for supporting MT systems.

2.2. Search Strategy

An overview of our search methodology and the number of articles collected at each step is shown in Figure 1 and described in detail below. To start the search, it was essential to determine search criteria that fit the purposes of our survey. Based on best practices [18–20], we defined the following selection criteria to classify the retrieved studies.

2.2.1. Inclusion criteria

The papers considered in our study were publications in English between 2000 and 2017. They had to satisfy at least one of the following criteria:

- a focus on distinguishing between ambiguous words in MT that use SWT.
- proposed and/or implemented an approach for MT using SWT.
- contain a combination of ontological knowledge with MT for handling structure divergence issues.

2.2.2. Exclusion criteria

None of the criteria below was to hold for the papers considered in this survey:

- not peer-reviewed or published.
- assessment methodologies published as a poster abstract.
- no use of SWT in MT for translating natural language sentences.
- not proposing an MT approach or framework which retrieves information using SWT.

2.2.3. Search queries

To address the research questions and criteria, we determined a set of keyword queries that allowed us to detect relevant studies for our survey. We used the following keywords: *machine translation, semantic web, ontology, linked data, disambiguation, methodology, and multilingual*. The choice of these keywords corresponds to the main keywords used by SW and MT works in their titles. Also, the keywords *multilingual* and *methodology* were identified to return papers matching the inclusion criteria. Therefore, they were combined in two search queries in order to retrieve the relevant research works.

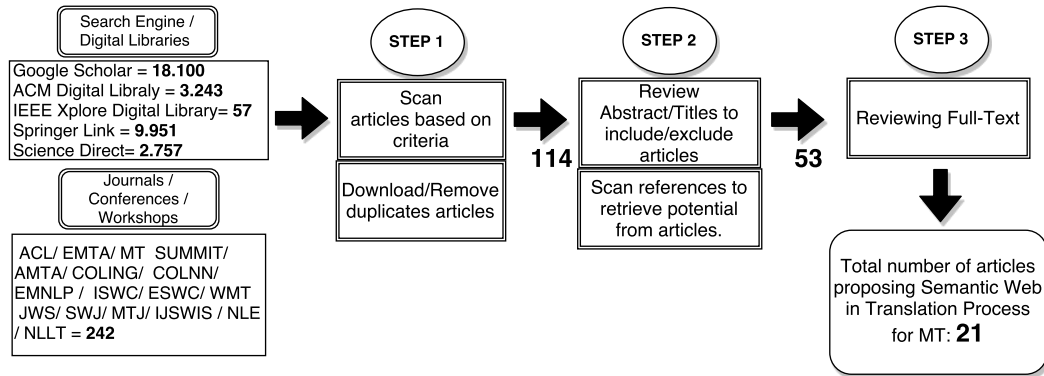


Figure 1: Steps followed to retrieve the systematic review results.

1. machine translation AND (ontology OR linked data OR semantic web OR disambiguation)
2. (methodology OR multilingual OR disambiguation) AND (linked data OR ontology OR semantic web OR machine translation)

Thereafter, we used the following search engines, digital libraries, journals, conferences, and workshops to find relevant publications.

Search engines and digital libraries:

- Google Scholar³
- ACM Digital Library⁴
- IEEE Xplore Digital Library⁵
- SpringerLink⁶
- ScienceDirect⁷
- MT-Archive⁸

Journals:

- Semantic Web Journal (SWJ)⁹
- Journal of Web Semantics (JWS)¹⁰
- Machine Translation Journal (MT)¹¹
- Natural Language and Linguistic Theory¹²
- Natural Language Engineering¹³

- International Journal on Semantic Web and Information Systems (IJSWIS)¹⁴

Conferences and associated workshops:

- Association for Computational Linguistics (ACL) [21–38]
- North American Association for Computational Linguistics (NAACL) [39–49]
- Empirical Methods in Natural Language Processing (EMNLP) [50–63]
- International Conference on Computational Linguistics (COLING) [64–72]
- International Association for Machine Translation (IAMT, AMTA, EAMT, MT Summit)¹⁵
- World Wide Web Conference (WWW) [73–89]
- International Semantic Web Conference (ISWC) [90–103, 103–105]
- Extended Semantic Web Conference (ESWC) [106–119]

2.3. Search Steps

The initial search based on the queries described above returned 34,350 publications. The subsequent processing of this set of publications was divided into three steps.

2.3.1. Step 1

This step ensures that the publications considered in the study abide by the selection criteria. Hence, we excluded publications that are not in English or do not contain any reference to SW and MT. Moreover, we excluded all publications that were not peer-reviewed, as well as works that were published as posters or abstracts. We scanned the articles manually based on the criteria presented above.

³<http://scholar.google.com/>

⁴<http://dl.acm.org/>

⁵<http://ieeexplore.ieee.org/>

⁶<http://link.springer.com/>

⁷<http://www.sciencedirect.com/>

⁸<http://www.mt-archive.info/>

⁹<http://www.semantic-web-journal.net/>

¹⁰<http://www.websemanticsjournal.org/>

¹¹<http://link.springer.com/journal/10590>

¹²<http://link.springer.com/journal/11049>

¹³<http://journals.cambridge.org/action/displayJournal?jid=NLE>

¹⁴<http://www.ijswis.org/>

¹⁵<http://www.mt-archive.info/srch/conferences-1.htm>

Thereafter, the bibliographic metadata of remaining publications was analyzed using the bibliography management platform Mendeley¹⁶ and 21 duplicates were removed.

2.3.2. Step 2

For this step, we reviewed the abstracts of the 114 articles returned by Step 1 based on the four research questions described in Section 2.1. 64 of the 114 articles were excluded for not using SWT. However, all 114 articles were documented as a reference source for potential future articles. To retrieve articles from references we adopted the following strategy:

1. We searched for the article title in Google Scholar and retrieved the “Cited By” articles.
2. We then read the abstract of each potential article found by searching the references of all 50 articles and by these means, found 3 more articles.

2.3.3. Step 3

With a total of 53 articles deemed potentially relevant for the survey, we read all articles completely to evaluate their suitability for our study. As a final result, we selected 21 articles published between 2000 and 2017, which are listed in Table 1. 10 of these 21 articles matched the criteria, which propose and/or implement MT using SWT. 6 of 21 matched the criteria for disambiguation processes in MT using SWT. 5 of 21 matched the criteria that focused on combining ontological knowledge with MT to handle syntactic divergences. Most of the remaining relevant articles are related to the translation of ontology labels. Although ontology label translation is an important task relevant to some of the articles, we do not consider them in this survey because ontology labels are single words or compounds rather than sentences.

3. Classification of MT Approaches

In this section, we give an overview of generic dimensions across which MT systems can be classified. This overview allows for a better understanding of the approaches retrieved as described above. A detailed description of the approaches is given in Section 3.2. Sequentially, we introduce the remaining dimensions. Afterwards, we present the open MT challenges pertaining to all MT approaches. Finally, we briefly introduce common MT evaluation metrics in order to provide a background to how MT systems are evaluated automatically.

3.1. Dimensions

We classify MT systems across three dimensions.

1. *Architecture*: From an architectural perspective, it is assumed that all MT paradigms could be subsumed under one architecture to model existing MT systems [4]. However, the architecture may be composed of more than one

approach and these approaches depend, for their operation, on the amount of available knowledge. For example, some approaches rely purely on statistics (SMT) while others use complex linguistic models (RBMT) to compute a translation.

2. *Problem space addressed*: Previous works (e.g., [141]) suggest that particular MT approaches are best suited to address particular types of problems. For instance, an approach for translating old Egyptian texts should rely on deep linguistics rules due to the lack of bilingual corpora. In contrast, translating large volumes of text is best carried out using statistics models because resolving many errors from hand-crafted rules requires a big human effort. Furthermore, the usage of statistics will depend on the language and availability of bilingual corpora for training.
3. *Performance*: A central challenge of MT is to create real-time MT solutions that achieve a high-quality translation of variable-nature texts, while being low in complexity to build. For example, while SMT performs well on long texts (paragraphs containing 100 words), it often fails on short sentences (e.g., social network comments and subtitles) [142] - mainly when a given SMT is built using large corpora and needs to translate text from different domains [4].

3.2. Architectures

Currently, the architectures of MT systems are subdivided into RBMT, SMT and EBMT. In addition, hybrid systems which combine RBMT with SMT have emerged over recent years. Figure 2 gives an overview of a generic MT architecture that may represent the workflow of all approaches. The left side of the triangle comprises generically of source text analysis, while the right side corresponds to the generation of target texts. Both sides of this generic architecture have four main steps. (1) A morphological step, which handles the morphology of words. (2) A syntactic step, which deals with the structure of sentences. (3) A semantics’ step, which considers the meaning of words and sentences. Finally, (4) An interlingua phase, which may be seen as a generic representation of source and target text either in RBMT (internal model) or SMT approaches (statistical model).

3.2.1. Rule-Based Machine Translation

At a basic level, RBMT approaches carry out a translation in the following manner: first, they parse the input text. Then they create an intermediary linguistic representation of the scanned text. They finish by generating text in the target language based on morphological, syntactic, and semantic mappings between the two languages. RBMT approaches can be divided into three categories: direct, transfer-based, and interlingua-based. In order to perform well, all of these approaches require extensive lexicons and large sets of rules designed by professional linguists.

¹⁶<https://www.mendeley.com/groups/7405201/semantic-web-machine-translation/papers/>

Table 1: List of the selected papers.

Citation	Title
C. Vertan [120]	Language Resources for the Semantic Web - perspectives for Machine Translation
W. Hahn and C. Vertan [121]	Challenges for the Multilingual Semantic Web
N. Elita and A. Birladeanu [122]	A First Step in Integrating an EBMT into the Semantic Web
C. Shi and H. Wang [123]	Research on Ontology-driven Chinese-English Machine Translation
N. Elita and M. Gavrila [124]	Enhancing translation memories with semantic knowledge
E. Seo et al. [125]	Syntactic and Semantic English-Korean Machine Translation using Ontology
P. Knoth et al. [126]	Facilitating Cross-Language Retrieval and Machine Translation by Multilingual Domain Ontologies
L. Lesmo et al. [127]	An Ontology based Architecture for Translation
A. M. Almasoud and H. S. Al-Khalifa [128]	A Proposed Semantic Machine Translation System for Translating Arabic Text to Arabic Sign Language
B. Harriehausen-Mühlbauer and T. Heuss [17, 129]	Semantic Web based Machine Translation
K. Nebhi et al. [130]	NERITS - A Machine Translation Mashup System using Wikimeta and Linked Open Data
J. P. McCrae and P. Cimiano [131]	Mining Translations from the Web of Ppen Linked Data
D. Moussallem and R. Choren [132]	Using Ontology-based Context in the Portuguese-English Translation of Homographs in Textual Dialogues
O. Lozynska and M. Davydov [133]	Information technology for Ukrainian Sign Language translation based on Ontologies
K. Simov et al. [134]	Towards Semantic-based Hybrid Machine Translation between Bulgarian and English
T.S. Santosh Kumar. [135]	Word Sense Disambiguation Using Semantic Web for Tamil to English Statistical Machine Translation
N. Abdulaziz et al. [136]	Towards an Arabic-English Machine-Translation Based on Semantic Web
J. Du et al. [137]	Using BabelNet to Improve OOV Coverage in SMT
A. Srivastava et al. [138]	How to Configure Statistical Machine Translation with Linked Open Data Resources
C. Shi et al. [139]	Knowledge-based Semantic Embedding for Machine Translation.
A. Srivastava et al. [140]	Improving Machine Translation through Linked Data.

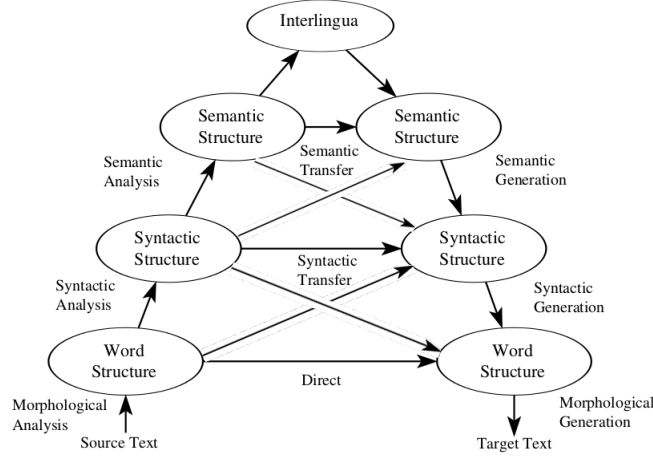


Figure 2: Generic MT Architecture - Vauquois triangle

3.2.1.1. Direct approaches. This family emerged with the first MT created by IBM [143]. Another translator which implemented this idea was Systran [144]. Commonly, direct approaches are word-based or dictionary-based, translating the words one by one. Hence, they translate the texts without considering the meaning variations in the words, which leads to a significant error rate. Thus, the direct translation is seen as the first step in modern MT systems and since it can easily be combined with other technologies, it is commonly used by hybrid MT systems.

3.2.1.2. Transfer-based approaches. Transfer-Based Machine Translation (TBMT) was created due to the obvious necessity of preserving meaning whilst translating. TBMT has three steps: analysis, transfer, and generation. In the first step, TBMT systems analyze the sentence structure of the source language and generate an internal representation based on linguistic patterns of the target language. Subsequently, TBMT systems translate only the text for both respective languages. To this end, TBMT

use three dictionaries during the translation process: two monolingual dictionaries (source language and target language) and a bilingual dictionary containing a mapping between the source and the target languages [145].

3.2.1.3. Interlingua-based approaches. The Interlingua approach relies on similar insights to those underlying TBMT. The main difference between them is the internal model which they rely upon. In contrast to TBMT approaches (where the target language plays a key role), Interlingua-based approaches rely on extracting a language-independent representation of the input text. Hence, this can be easily adapted to translating into multiple target languages. State-of-the-art interlingual approaches rely most commonly on morphological, syntactic, and semantic rules based on a grammatical framework [146]. These are more accurate than comparable previously mentioned approaches (i.e., direct and TBMT). In addition, a direct beneficial consequence of the interlingual approach is the time-efficient portability of its framework to other languages. This approach is widely used

by linguists for morphologically rich languages because it allows them to choose the better language representation of a translation model based on the source text. On the other hand, to achieve a high-quality translation with Interlingua, the operator must carry out the translation within a specific domain.

3.2.2. Statistical Machine Translation

SMT relies upon the intuition that RBMT shortcomings can be addressed using experience. Commonly, SMT approaches acquire this experience from previous translations. These previous translations are collected from bilingual corpora, either parallel or comparable. They are crucial for the performance of SMT approaches. A bilingual parallel corpus is comprised of a source text and its respective translation. In contrast, a comparable corpus does not contain an exact translation of a source text, but a similar corpus in another language which may share the same topic, size or given time. SMT approaches heavily depend on Machine Learning (ML) techniques including supervised, unsupervised, and semi-supervised algorithms to compute a statistical translation model from the input corpus for use in subsequent translations. Most commonly, the goal of SMT approaches is simply to detect the translation that achieves the maximum probability or score for a given translation pair. SMT requires well-suited parallel or comparable bilingual corpora to achieve high accuracy. Comparable corpora can be used to get more terminological knowledge into a certain SMT system, but the SMT still needs an underlying language model built on parallel data. Hence, the translation quality directly depends on the language model trained on a given target side of the parallel corpus, which is a subset of the respective bilingual corpora.

Every SMT system shares at least three common steps. First, an alignment between the parallel or comparable corpora is necessary. Both source and target corpus are aligned in order to provide a mapping between each respective translation. When parallel corpora do not exist, there are ways to handle comparable corpora using algorithms which take alignment probabilities into account. Although it may affect the quality of a given SMT, this is a common task when there are insufficient reference translations. Second, a translation model needs to be created and trained over the alignment previously done, thus being responsible for translating the content from source to target language. At training phase, an underlying model is created which contains statistical frequencies of words and may contain syntactic information (from a hierarchy model or manually inserted) about both languages. Once the model has been created, the source text can be processed. The text is translated into the target language based on a function akin to a probability or score distribution contained in the model. Finally, the last step is called decoding, which is essentially a search function that accesses the translation model by getting all the translation candidates and providing a ranked list of possible translations. The language model which is created from a reference translation usually made by humans guarantees the fluency of a certain target language [4]. The following five sub-approaches exist in SMT.

Word-based - This approach was the first statistical one created by IBM which contains at least five IBM models. The

Word-based approach basically translates each word at a time based on its frequency computed by the translation model over the entire training data. By ignoring multiple meanings of a given word (e.g., polysemous or homonymous words), the approach can generate wrong translations. Considering this weakness, Yamada and Knight[147] then created the **Phrase-based** approach which consequently was improved by Koehn [148]. It translates based on phrases which correspond to more than one word. Thus, this approach is able to consider the surrounding context of each word when dealing with ambiguous words. The *Phrase-based* approach is considered a huge advancement with respect to MT approaches. However, problems such as reordering and ambiguity still exist especially when translating multi-domain contents, which basically do not have a vocabulary overlap.

Regarding the remaining errors, one remedy found was to include linguistic rules in the translation model. Consequently, the **Syntax-based** and **Tree-based** approaches appeared. They combine linguistics rules with statistical models, but the linguistic rules used by both approaches are different from those in RBMT. The difference lies in the limitations imposed by applying some complex linguistic rules in a polynomial efficient time. Thus, some crucial linguistic rules are not considered. The *Syntax-based* approach uses part-of-speech tagging, which is responsible for decreasing structural problems while *Tree-based* models attempt to resolve the reordering problem using dependency parsing trees between languages. This combination solves basic and important problems caused by the structure of languages in *Phrase-based MT*. In spite of *Tree-based* approaches showing notable improvements, it skips a large number of necessary parsing rules, thus continuing to produce material errors [4].

Recently, a new statistical approach called **Neural Network-based** (also known as NMT)¹⁷ has gained significant popularity [149, 150]. Although NN techniques are not essentially novel, they have been widely exploited since Google published their research [151] on beneficial improvements applying NN on sequence-to-sequence models¹⁸. The structure of a given NMT system is much simpler than the well-known *Phrase-based SMT* in terms of components. In NMT systems, there are no separate models (e.g., language model, translation model), rather, they usually consist of one sequence model responsible for encoding and decoding the words. This sequence model learns a context vector created from the sources and target sentences for translating the texts. The context vector, i.e., embeddings, is an important part as it represents the continuous space representation of words and allows the sequence model to predict similar words. Despite some researchers claiming that NMT may practically solve many of the weakness of SMT systems, it is still recent research and, as a statistical approach, still suffers from some well-known statistical problems [15] that are described in Section 3.3.

¹⁷see new chapter at Koehn's book <http://statmt.org/mtma16/uploads/mtma16-neural.pdf>

¹⁸<http://www.statmt.org/survey/Topic/NeuralNetworkModels>

3.2.3. Example-based Machine Translation

Similar to statistical approaches, EBMT use bilingual corpora, but they store the data by example sentences. The training phase of EBMT approaches imitates a basic memory technique (analogy) of human translators and is akin to filling the database of a translation memory system [152]. Here, EBMT approaches split the source text of a training corpus into sentences and align each of these sentences with the corresponding target sentences from the same training dataset. When an EBMT is used, the known source sentences are fetched first. If any of these sentences occur in the input, the machine replaces it by the corresponding translation. If during the translation an unknown word occurs in a sentence (i.e., a word which was not seen in the training data), the word is not translated. This is clearly the main limitation of EBMT approaches, which is addressed by hybrid MT systems. If several translations are available, the translation process chooses the target sentence based on a ranking algorithm. As EBMT systems are related to memory techniques, they require large physical memory to store the translated sentences. Although the MT community has moved forward with this approach, it is quite interesting and easily combined with the others.

3.3. Problem space addressed by MT

According to [141], some MT approaches may perform better than others for translating contents depending on the problem, language and how much bilingual content is available. Although RBMT approaches are still currently used due to the difficulty of finding bilingual or comparable corpora containing syntactic information for some morphologically rich languages, the MT community has practically moved on from RBMT approaches because of the complicated extension of their linguistic rules. It has occurred due to the exponential number of research works on SMT, based on languages which are widely spoken around the world and consequently have more bilingual data, such as English, French and Chinese. Thus, the creation of hand-crafted rules from these languages is no longer needed, as the ML algorithms seemed to resolve the problems.

Additionally, Koehn [4] states that acquiring comparable corpora is made simple by using crawling techniques on the Web. However, the process of alignment required by SMT approaches is substantially harder, and even more so without an explicit well-defined Web format. For instance, there is a task created by the well-known MT workshop with the goal of aligning sentences automatically from Web pages in order to create comparable corpora¹⁹. The results and the training phase of this task confirm the difficulty of the process. For example, the reasonable difference between possible and training pairs where the training pairs are 1,624 and possible pairs are 225,043. Possible pairs are pairs which exist from a human perspective and may be found by an algorithm. In contrast, training pairs are accurate pairs which are given for training the candidate algorithms. Although the results of this task are promising, the evaluated systems require improvements for creating a real MT

training data. Also, most comparable corpora are limited in terms of domains (e.g politics, technology and financial).

3.4. MT performance and effort

All MT approaches have advantages and disadvantages w.r.t. quality and efforts. In Table 2, we compare the approaches presented in Section 3.2, considering the dimensions stated previously.

The main weakness of RBMT systems lies in their complexity of building the models, which is associated with the manual processing of deep linguistic knowledge. For example, Interlingua approaches require a significant time to create the internal representation by linguists [153]. Linguistics professionals commonly need to annotate the rules and structure manually. Although RBMT are clearly rather expensive approaches, grammar problems may be found easily by linguists. Note that the modification of current rules does not guarantee better results. Linguists even may diverge from some rules, thus causing the creation of inconsistent rules. Consequently, the creation of accurate RBMT has come to be regarded as a very difficult task with many bottlenecks.

On the other hand, SMT systems do not require complex linguistic rules. However, the main challenge is reaching a good translation quality over multi-domain texts. Commonly, SMT systems are trained using reference translations by which ML algorithms are able to analyze the data and find patterns by themselves, thus being able to translate text without any rules created by humans. Although some basic linguistics mistakes have been solved by *Tree-based* and *Neural Network-based* approaches, the lack of complex linguistic rules still causes ambiguity problems (e.g., errors on relative pronouns) [154]. An additional problem of the latter approach is the complexity of performing error analysis over outputs. For instance, NMT systems do not provide an easy way to find problems in feasible time [155, 156]. In spite of NMT approaches have currently been achieving better results than the others, they have similar drawbacks and are much less interpretable than SMT. Additionally, NMT approaches struggles to deal with out-of-vocabulary (OOV) words (rare words) since it has a fixed vocabulary size. However, the community has been combining efforts in order to handle this problem by using character-based models or sub-words units, which are able to predict unforeseen words[157–159]. Therewith, it is still an open problem which is related to the disambiguation of words. Furthermore, despite the advances in NMT approaches, a significant amount of effort is being invested in improving the scalability of RBMT approaches in order to achieve a higher performance than their counterparts. Hence, RBMT is still regarded as essential to high-quality translation, even more for rich morphological languages.

3.5. Open MT Challenges

The following most problematic unresolved MT challenges, according to our point of view, are still experienced by the aforementioned MT approaches :

¹⁹<http://www.statmt.org/wmt16/bilingual-task.html>

Table 2: MT Approaches Comparison

Rule-based	
Pros	Cons
Deep linguistic knowledge (quality)	Requires linguistic rules and dictionaries (effort)
Easy to perform error analysis (effort)	Human language inconsistency (quality)
	Expensive to extend and improve (effort)
Statistical	
Pros	Cons
No complex processing of linguistic rules (effort)	Always require parallel text (quality, effort)
Less human resources cost, no linguists required (effort)	No linguistic rules causes syntactic/semantic errors (quality)
Applicable to any pair of languages (effort)	Difficult to perform error analysis (effort), especially for NMT
Models trained with human translations (quality)	Preprocessing noisy training data (effort)

1. *Complex semantic ambiguity*: This challenge is mostly caused by the existence of homonymous and polysemous words. Given that a significant amount of parallel data is necessary to translate such words and expressions adequately. MT systems commonly struggle to translate these words correctly, even if they are built on from 5- or 7-grams. For example, “John promises to keep his room tidy” and “John has some promises to keep until he is trusted again”. Although the meaning of both are clear to humans, these sentences for SMT systems are statistically expensive and prone to failure²⁰. Additionally, for translating the simple word “bank”, context information is essential for determining which meaning to assign to it.
2. *Structural divergence*: By definition, structural reordering is reorganizing the order of the syntactic constituents of a language according to its original structure [154]. It in turn becomes a critical issue because it is the core of the translation process. Every language has its own syntax, thus each MT system needs to have adequate models for the syntax of each language. For instance, reordering a sentence from Japanese to English is one of the most challenging techniques because Japanese sentences do not contain spaces between their characters and one Japanese character often groups multiple meanings of English words.
3. *Tense generation*: A large number of languages display a complex tense system. When confronted with sentences from such languages, it can be hard for MT systems to recognize the current input tense and to translate the input sentence into the right tense in the target language. For instance, some irregular verbs in English like “set” and “put” cannot be determined to be in the present or past tense without previous knowledge or pre-processing techniques when translated to morphologically rich languages, e.g., Portuguese, German or Slavic languages. Additionally, the grammatical gender of words in such morphologically rich languages contributes to the problem of tense generation where a certain MT system has

to decide which inflection to use for a given word. This challenge is a direct consequence of the structural reordering issue and remains a significant problem for modern translator systems.

Additionally, there are five MT open challenges posed by Lopez and Post [160] which we describe more generically below.

- (1) Excessive focus on English and European languages on MT approaches as one of the involved languages and poor research on low-resource language pairs such as African, South America languages.
- (2) The limitation of SMT approaches for translating across domains. Most MT systems exhibit good performance on politics due to the large amount of data provided by the European Union. In contrast, translations performed on sports and life-hacks commonly fail.
- (3) How to translate the huge amount of data from social networks that uniquely deal with no-standard speech texts from users (e.g., tweets).
- (4) The difficult translations among morphologically rich languages. This challenge shares the same problem with the first one, being that most research work focuses on English as one of the involved languages. Therefore, MT systems which translate content between, for instance, Arabic and Spanish are rare.
- (5) For the speech translation task, the parallel data for training differs widely from real user speech.

The challenges above are clearly not independent, which means that addressing one of them can have an impact on the others. Since NMT has shown impressive results on reordering, the main problem turns out to be the disambiguation process (both syntactically and semantically) in SMT approaches [4].

3.6. MT Evaluation Metrics

An evaluation of a given MT system may be carried out either automatically or manually. Generally, the MT community has opted to use automatic metrics for decreasing human efforts and time. Once an MT system has shown promising results from a certain automatic evaluation metric, the output of this MT system is then evaluated by a human translator. A common process of automatic evaluation is composed of the source text (input), target text (output produced by an MT system which is also called hypothesis) and the reference translation of the source text (output created by a human translator). The reference translation is compared automatically against the

²⁰See a complete discussion about the problem: <http://tinyurl.com/yck5ngj8>

target text using a given evaluation metric. There are plenty of automatic MT evaluation metrics. However, below we introduce only the most important metrics which were also used for evaluating the surveyed papers. Such metrics enable a scientific comparison between the quality of different MT systems.

- **BLEU** was created by Papineni [161] as an attempt to decrease the professional translation efforts for evaluating the performance of MT systems. BLEU is widely chosen for evaluating MT outputs due to its low costs. BLEU uses a modified precision metric for comparing the MT output with the reference translation. The precision is calculated by measuring the ngram similarity (size 1-4) at word levels. Also, BLEU deals with the number variability of useless words commonly generated by MT systems. Thus, it applies a penalty by comparing the length of the MT output with the reference translation. However, the main weakness of BLEU is its difficulty handling semantic variations (i.e., synonyms) while performing the ngram similarity.
- **NIST** was designed by Doddington [162] to address some weaknesses of BLEU, upon which it is based. Instead of attributing the same weight for each word in a sentence, NIST gives more weight to a rare word when matched by n-gram. It also modifies the penalty applied by BLEU on the comparison of the MT output with the human translation, reducing the impact of small variations on the overall score.
- **METEOR** was introduced by Banerjee and Lavie [163] to overcome some weaknesses of BLEU and NIST, for example, the lack of explicit word-matching between translation and reference, the lack of recall and the use of geometric averaging of n-grams. The goal of METEOR is to use semantic features to improve correlation with human judgments of translation quality. To this end, METEOR considers the synonymy overlap through a shared WordNet synset of the words.
- **TER** is different from the aforementioned metrics. TER measures the number of necessary edits in a MT output to match the reference translation exactly. The goal of TER is to measure how much effort is needed to fix an automated translation to make it fluent and correct [164]. The edits consist of insertions, deletions, substitutions and shift of words, as well as capitalization and punctuation. The TER score is calculated by computing the number of edits divided by the average referenced words.
- **MEANT** was firstly created by Chi-kiu Lo in 2011 [165] for alleviating the semantic correlation deficit between the reference and MT outputs from well-known MT metrics such as METEOR and BLEU. Although METEOR has been created to deal with the semantic weakness of BLEU (i.e synonyms), it ignores the meaning structures of the translations. MEANT outperforms all the existing MT metrics in correlation with human adequacy judgment, and is relatively easy to port to other languages.

MEANT requires only an automatic semantic parser and a monolingual corpus of the output language, which is used to train the discrete context vector model for computing the lexical similarity between the semantic role fillers of the reference and translation. Recently, a variation of MEANT has been created by Chi-kiu Lo et. al [166] which nowadays is the state-of-the-art of semantic MT evaluation metrics. This new version of MEANT replaced the discrete context vector model with the continuous word embeddings in order to further improve the accuracy of MEANT. The accuracy of MEANT relies heavily on the accuracy of the model that determines the lexical similarities of the semantic role fillers.

4. Surveyed Papers

In this section, we describe how the surveyed articles work and conclude with suggested directions for using SWT in MT²¹.

4.1. Selected Research Works

This section describes all surveyed articles according to the MT approaches described in Section 3 in order to provide continuity for the reader. Table 3 presents a comparison of all surveyed articles, along with their MT method and applied SWT. The column *MT approach* represents which kind of MT was chosen for handling the translation process. The column *SW method* denotes what SWT were used to extract the knowledge contained in a given SW resource, for instance, semantic annotation technique, SPARQL queries, and reasoning. The column *Resource* shows what kind of resource was used to acquire the SW knowledge, in this case ontology files or Linked Open Data (LOD), which means a Knowledge Base (KB) such as DBpedia or BabelNet. The column *Evaluation* illustrates the evaluation process that was applied for measuring the quality of the work, e.g., whether the evaluation was performed by humans or using automatic evaluation metrics.

4.1.1. Direct

- Heuss et al. combined SWT as post-editing technique with the direct approach in their work. Post-editing technique involves fixing mistakes from a given output by choosing the right translated word or order. Although this technique is commonly used by a professional translator or a linguist, its automated implementation has been widely researched recently in order to reduce human efforts. The works [17, 129] propose an method for retrieving translations from a domain ontology. The approach performs SPARQL queries to search translations of a given word. The ontology uses SKOS vocabulary [167] to describe its multilingual content. SKOS is a common model for describing concepts in SW. It uses the *prefLabel* property to assign a primary label to a particular concept and *altLabel* for alternative names or translations.²²

²¹The description of the articles may not follow a standard due to the lack of details in some works.

²²<https://www.w3.org/TR/skos-reference/>

Table 3: Details of surveyed articles

Citation	Year	MT approach	SW method	SW resource	Evaluation
C. Vertan [120]	2004	EBMT	Annotation	Ontologies	None
N. Elita and A. Birladeanu [122]	2005	EBMT	SPARQL	Ontologies	None
W. Hahn and C. Vertan [121]	2005	EBMT	SPARQL + Annotation	Ontologies	None
C. Shi and H. Wang [123]	2005	None	Reasoner	Ontologies	None
N. Elita and M. Gavrilă [124]	2006	EBMT	SPARQL	Ontologies	Human
E. Seo et al. [125]	2009	None	Reasoner	Ontologies	None
P. Knoth et al. [126]	2010	RBMT or SMT	Annotation	Ontologies	Human
A. M. Almasoud and H. S. Al-Khalifa [128]	2011	TBMT + EBMT	SPARQL	Ontologies	Human
L. Lesmo et al. [127]	2011	Interlingua	Annotation	Ontologies	Human
B. Harriehausen-Mühlbauer and T. Heuss [17, 129]	2012	Direct	SPARQL + Reasoner	Ontologies	Human
K. Nebhi et al. [130]	2013	TBMT	Annotation	LOD	None
J. P. McCrae and P. Cimiano [131]	2013	SMT	Annotation	LOD	Human
D. Moussallem and R. Choren [132]	2015	SMT	SPARQL	Ontologies	Human
O. Lozynska and M. Davydov [133]	2015	RBMT	Annotation	Ontologies	Human
K. Simov et al. [134]	2016	RBMT + SMT	SPARQL	LOD	Automatic
T.S. Santosh Kumar. [135]	2016	SMT	SPARQL	Ontologies	Human
N. Abdulaziz et al. [136]	2016	SMT	SPARQL	Ontologies	Human
J. Du et al. [137]	2016	SMT	SPARQL	LOD	Automatic
A. Srivastava et al. [138]	2016	SMT	SPARQL + Annotation	LOD	Automatic
C. Shi et al. [139]	2016	NMT	Annotation	LOD	Automatic + Human
A. Srivastava et al. [140]	2017	SMT	SPARQL + Annotation	LOD	Automatic

Once SPARQL queries have retrieved the translations, a reasoner infers a relationship between the source and target words based on its properties contained in the ontology. The authors manually marked parts of the data as triggers. Hence, the inference rules were basically done manually. Although this work provides important insights, the evaluation of its output is insubstantial as the authors evaluated only one sentence to validate their approach. The given explanation for this weak evaluation is that the reasoner is not fast enough for large texts and for executing on more than one sentence.

4.1.2. Transfer-Based

- In NERITS [130], the authors presented an MT system with additional information about the translated text. They used DBpedia for providing concepts about each word, similar to the semantic annotation technique. A semantic annotation technique involves annotating a given word or text, adding information/concepts about it from a given KB. The goal of NERITS is to provide more knowledge for users using SW. The authors chose a *Transfer-based* approach for translating the content. The translation process begins performing Named Entity Recognition (NER) [168] through a tool called Wikimeta to deal with the variations of entities. The NER technique is responsible for recognizing the entities and their respective types. For instance, Microsoft is an organization and Bill Gates is a person. Thus, Wikimeta is responsible for linking each recognized entity with a given resource within the knowledge base. Although the authors contended for the use of a post-editing technique, the SW method applied here does not edit or improve the output, it just provides concepts for helping the user to understand and assimilate the translation. The authors stated that no current MT systems provide conceptual knowl-

edge about the translated words, they only present the crude translation. Their goal was to describe how users can learn about languages combining MT with SW. The authors stated that their proposal could not be evaluated with automatic MT metrics because they did not improve the translation process, but annotated the translations providing additional knowledge.

- O. Lozynska and M. Davydov [133] developed a MT system for translation of Ukrainian Sign Language (USL). The authors chose the Transfer-based MT approach because of the lack of parallel data for statistical translation. Additionally, the authors argued that a rule-based approach, along with ontologies, is best suited for implementing the rules of sign languages. To this end, the authors used a grammatically augmented ontology from a diversity of domains such as education, nature and army. The ontology was mainly used for supporting a given parser in the extraction of syntactic and semantic rules. These syntactic-semantic rules enable a deep analysis of sentences thus avoiding the problem of ambiguity in USL. The crucial contribution according to authors was the creation of a new domain-specific language based on the ontologies which may be further used for editing and processing future works in the translation of USL using ontologies. The evaluation was carried out manually by linguists once the sign languages are difficult to be evaluated automatically. The results were quite promising, the ontology contributed to 19% of improvements in the analysis of Ukrainian signs and 35% in the generation of Ukrainian natural language compared to baseline from related works.

4.1.3. Interlingua

- Lesmo et al. [127] presented an approach for translating from the Italian language to Italian Sign Language. The

authors translated the content using the interlingual approach with SWT. The goal of using SWT, in this case, an ontology, is to discern the syntactic ambiguity of a given word caused by the automatic syntax-semantic interpretation within the generation step at the translation process. To this end, the authors used a very limited domain, a weather forecast ontology, for dealing with the variety of specific terms. Therefore, the authors assumed that a certain word meaning may be expressed by ontology nodes. Thus, the relationship between nodes which are ontology properties may resolve the syntax-semantic issues at translating a sentence. Afterwards, the authors converted the ontology structure into first-order logic and included the logic forms using the OpenCCG tool into the interlingual language model. Therefore, the translation starts by performing a syntactic analysis step which is based on dependency trees. Afterward, each word is annotated with its respective lexical meaning from the ontology, thus creating an ontological representation. This representation is then interpreted for determining which path (i.e., meaning) to follow and then translating the words correctly. The Interlingua approach was chosen because a translation of sign language requires deep linguistic expertise. Finally, the authors raised the problem of the lengthy time taken to translate due to the many ambiguity issues related to sign language and concluded that the approach requires further evaluation.

4.1.4. Statistical

- J. P. McCrae and P. Cimiano [131] extracted English-German translations from LOD. They used these results to improve the WSD inside SMT. The authors used the well-known SMT system called Moses [169], inserting the results retrieved from LOD into the phrase table created by Moses. The frequency table is used to select the best meaning (i.e., translation), thus discerning among various source meanings to arrive at a unique target meaning. Each word mined from LOD is queried in the Moses frequency table. If the word is not in the table, they insert the best-fit word (1.0) into the table. They did not achieve good results with automatic evaluation using BLEU [161]. The outcomes showed no improvement against Moses as a baseline system. Baseline got 11.80 and baseline+LD got 11.78. However, the manual evaluation done by linguists showed a significant improvement of almost 50% percent in the output translation.
- Moussallem and Choren [132] presented a novel approach to tackle the ambiguity gap of message translations in dialogue systems. The translations occurred between Brazilian Portuguese and English. Currently, submitted messages to a dialogue system are considered as isolated sentences. Thus, missing context information impedes the disambiguation of homographs in ambiguous sentences. Their approach tries to solve this disambiguation problem by using concepts in different existing ontologies. First, the user log is parsed in order to find out the re-

spective ontology that matches the dialogue context. Using the SKOS vocabulary, the ontology that returns the most results for each verb or noun is used as context. When the SMT system returns a translation indicating a homonymous word (i.e., many different possible translations), this method queries the word in the ontology using SPARQL and replaces the target word accordingly. The authors evaluated their approach manually using empirical methods. The ontologies were Music ontology²³ and Vehicle ontology²⁴. Regarding its focus on dialogue systems, the work fails to translate slang or expressions that are common in dialogues. Since such sentences are rarely in well-structured form, the translations often contain structural errors. Also, the context is fixed during a dialogue, so a topic change is not reflected by the system²⁵.

- Neama Abdulaziz et al. [136] extended the previously described approach presented by Moussallem et al. for Arabic-English translations. As its main extension, this work includes a dependency tree parser because of the rich morphological structure of Arabic. Thus, the SMT approach used by authors is *Tree-based*, which inserts the tree as statistical rules. In contrast, during the common training phase of SMT, the dependency rules are attached according to the sent message. The authors use the MS-ATKS tool for analyzing the syntactic structure of messages and also a domain ontology on the Quran. Once this work has been applied to dialogue systems, the evaluation is carried out empirically by humans. The authors propose to apply different automatic metrics as further plans in order to evaluate additional aspects of this work.
- Santosh Kumar T.S. [135] proposed an approach to address lexical disambiguation in the translation of proper nouns from English to Dravidian languages such as Tamil. To this end, the authors created a corpus containing only ambiguous sentences for testing their approach. They used Google Translate as a SMT system because, in accordance with the state-of-the-art, Google MT system has the best translation model for translating from English to Tamil. The approach preprocessed ambiguous sentences using an NER tool for recognizing persons. Additionally, they relied on FOAF ontology in RDF structure for supporting the translation. This ontology contains information about a large number of names in Tamil. Due to the lack of resources in the Tamil language, which are required for automatic metrics such as BLEU, the evaluation was carried out manually. It presented positive outcomes where the professional translator confirmed the capability of SWT for supporting translations of entities among morphologically rich languages.
- Jinhua Du et al. [137] created an approach addressing the problem of OOV words. These kinds of words do not

²³<http://musicontology.com/>

²⁴<http://www.heppnetz.de/ontologies/vso/ns>

²⁵<https://github.com/DiegoMoussallem/judgemethod>

appear in the translation table of a given SMT approach such as *Phrase-based*. Commonly, they are named entities which often appear on the Web, such as persons and organizations, but they can also be common words like “kiwi” which is highly ambiguous. Therefore, the authors proposed three methods to deal with the OOV words problem using a SW resource called BabelNet. The respective methods are: (1) Direct Training, which retrieves every pair of source and target words, creating a dictionary to use during the training phase. (2) Domain-Adaption, which recognizes the subject of source corpus and applies a topic-modelling technique as Moussallem et al. have done. Hence, the found subject adapts the target corpus for a specific domain, gathering the information from BabelNet. According to the authors, these first two methods did not perform well, so they decided to apply BabelNet as (3) Post-processing technique. Therewith, they used a SMT decoder in order to recognize OOV words which were not translated beforehand. Subsequently, they performed SPARQL queries through BabelNet API [170] to retrieve translations of these words. As in previously surveyed works, they used Moses as a baseline for a SMT system to perform experiments. Additionally, they chose Chinese, English and Polish languages for translating the contents and they also decided to evaluate the translations from their system using the automatic metrics BLEU and TER. The evaluation showed unstable results using BabelNet. However, it also uncovered a promising way to rectify the OOV problem by looking for unknown words in LD. The authors intend to investigate different forms of using SWT in MT systems as a future work.

- A. Srivastava et al. [138] implemented a novel framework which translates named entities in SMT systems using LOD resources. The framework is akin to the approach of J. P. McCrae and P. Cimiano [131] and it uses Moses as a SMT baseline system. Natural Language Processing Interchange Format (NIF) vocabulary is used as interchanging format for converting natural language sentences to SW structure (i.e., triples). Then, the authors used DBpedia Spotlight [171] to recognize entities, thus facilitating their translation. Once the entities are recognized, their respective translations are gathered using SPARQL through the DBpedia endpoint. The translation of entities is marked using XML format and inserted into a Moses translation table. These markings avoid Moses having to translate the entities by its own probabilistic model and forces Moses to select the translations retrieved from LOD resources. The evaluation was carried out using the IT domain from the MT workshop,²⁶ which consists of 1.000 sentence translations. This task uses BLEU and TER for measuring the performance of a given MT system. Their LD-based framework showed

a significant improvement of 12% in comparison to the Moses baseline. BLEU increased by 0.8% and TER decreased by 3.2%. The authors dubbed their framework “SW-aware MT system”. Although they provided links to projects related to this framework, there are no links to their implementation.

- C. Shi et al [139] built a semantic embedding model relying on knowledge-bases to be used in NMT systems. The work is dubbed Knowledge Base Semantic Embedding (KBSE) which consists of mapping a source sentence to triples and then using these triples to extract the internal meaning of words to generate a target sentence. The mapping results in a semantic embedding model containing KB triples which were responsible for gathering the key information of each word in the sentences. Therefore, the authors investigated the contribution of KB to enhance the quality translation of Chinese-English MT systems. To this end, they applied KBSE in two domain-specific datasets, electric business, and movies. The evaluation was two-fold. First, they compared KBSE with a standard NMT system and also with Moses as SMT system by using BLEU as an automatic evaluation metric. Second, they selected humans to manually evaluate the translations. Additionally, the authors used an external named entity translator to get the translation of English entities into Chinese. Moreover, they included this entity translator in the evaluation of the other MT systems for a fair comparison. The results of KBSE were quite promising, BLEU showed an improvement of 1.9 points (electric) and 3.6 (movie) when compared to the standard encoder-decoder NMT system. Additionally, the KBSE method got much higher results than using the Moses toolkit. This work shows that a given neural model, when trained using semantic information gathered from a KB, is able to memorize the key information of source sentences. Also, their model rarely made grammar mistakes as the authors expected because of the strong learning ability of Gated Recurrent Unit [172]. Moreover, KBSE presented some errors at translating entities due to the external entity translator. Furthermore, since KBSE comprises two separate models, when an error appears at the source part, it can not be corrected in the target part.
- A. Srivastava et al. [140] mixed approaches from their last work [138] with some strategies implemented by Jinhua Du et al. [137] and the approach implemented by J. P. McCrae [131]. This work therefore comprises of three strategies for using LD with Moses as a SMT system. In the first strategy, the authors used the LD resources as dictionaries for word alignment. Thus the translation models contained knowledge from the LD resources and also from bilingual corpora. Hence, the Moses decoder is able to decide which translation of a given word to choose. This strategy is akin to J. P. McCrae’s [131] work. The second strategy relied on their former work, [138] which forced the Moses decoder to retrieve the translation of a given named entity by performing Entity Link-

²⁶<http://www.statmt.org/wmt16/it-translation-task.html>

ing (EL) along with SPARQL queries from LD. The last strategy was inspired by Jinhua Du et al.'s [137] work. It applied a post-editing technique for correcting the OOV words, which means untranslated words in MT output. The authors evaluated their approach using BabelNet, DBpedia and JRC names as LOD resources on the WMT12 dataset²⁷. The evaluation showed only modest improvements by BLEU and TER metrics because both deal poorly with semantics, i.e., synonyms. Therefore, the real contribution of LD in this work was made clear when the evaluation was performed by humans.

4.1.5. Example-Based

EBMT was the first methodology proposed to work alongside SWT because of its architecture. The EBMT process is simpler than other methods, thus facilitating its combination with other technologies. All works discussed in this section were carried out by a single research group. However, the research was discontinued.

- Vertan [120] presented an architecture based on EBMT which retrieves word meanings using semantic annotation from ontologies. As SW was in its infancy in 2004 when this work was undertaken, it proposed an architecture but did not implement it or give details properly. Thus, it is unclear how the semantic annotation actually helped the translation process.
- Her second work with Hahn [121] showed how semantic annotations could be used in MT systems. They explained how the properties in Resource Description Framework (RDF) data structures could support the annotation of words in several languages. Vertan and Hahn presented the same architecture of Vertan's previous work [120], but did not show the process of evaluation.
- A year later, Elita et al. [122] proposed a prototype of EBMT when SW was more concrete, which queried sentences from ontologies. The sentences were extracted from the text and queried through SPARQL endpoints instead of common databases. The translation was only provided by the ontology, which retrieved exactly one translation for each source sentence. Consequently, this work showed how Vertan's architecture could be implemented [120]. However, no evaluation was provided.
- Subsequently, N. Elita and M. Gavrilă [124] used an ontology to map existing concepts in a source text using NER and summarization techniques. The authors used five languages to prove their method. This approach showed how an ontology can support an automatic WSD process in MT. The authors stated that there was no need to analyze the text syntactically. However, this lack of analysis prevented the approach from handling inflections properly, which is a requirement for achieving good transla-

tions and thus a negative point of this work. The evaluation was done manually and demonstrated solid improvements only on translation templates, which their approach identified beforehand, but failed to present a comparison to other *example-based* approaches.

4.1.6. Hybrid

Whilst the combination of multiple MT approaches is already a challenge, three works were found that integrate a hybrid approach with SWT.

- Almasoud et al. [128] mix the translation process of TBMT (a rule-based approach) with EBMT (a corpus-based one) while using a domain ontology. This work translates from the Arabic language to Arabic Sign language. According to the authors, TBMT was chosen because a sign language requires deep linguistic knowledge (like [127] did in subsection 4.1.3). First, the text is converted into a representation model based on Arabic sign language rules, then the model is translated into signals. The ontology which belongs to the religion domain is applied in a similar fashion to the WSD task, exploiting its semantic knowledge. Then, every word is searched in the ontology to find its respective sign. In the case where there is no sign for a certain word, the SignWriting corpus is used to retrieve respective synonyms. Like many other works in this survey, this work fails to provide a detailed evaluation. The authors argued that an evaluation with automatic metrics is not possible because these do not provide measures to evaluate sign languages. Thus, they performed a manual evaluation, but did not provide any measure of improvement.
- Knoth et al. [126] presented an approach combining Cross-Language Information Retrieval (CLIR) and MT approaches for gathering translations of specific terminologies from domain ontologies. CLIR is a technique for retrieving contents from languages other than the language used for searching. They did not mention which kind of RBMT and SMT method they combined. Their approach is divided into two phases: (1) The initialization phase is responsible for creating the monolingual ontology and generating the lightweight multilingual ontology using a given RBMT system. To do this they first collected the monolingual text from the European Government and built a simple ontology using the SKOS vocabulary. Using RBMT, they translated the monolingual terms into nine European languages, thus creating a multilingual lightweight ontology. This multilingual ontology is then evaluated by domain experts, concluding the first step. (2) The bootstrapping phase then applied CLIR techniques by querying terms through SPARQL. Multilingual terms were used to create parallel corpora for each of the nine languages in order to train the SMT. Regarding the parallel corpora, they extracted translation pairs and updated the terms when a new document was submitted. Their approach allows the user to decide which domain and language to use.

²⁷<http://www.statmt.org/wmt12/>

The authors emphasized that the CLIR method can be adopted by any MT system. Furthermore, they stressed that multilingual ontologies support translations between any pair of languages. They too did not perform a proper evaluation of their architecture.

- Simov et al. [134] aimed to create a semantic-based hybrid MT system between Bulgarian and English in the domain of Information Technology. Their system supports the automatic identification of appropriate answers to user questions in a multilingual question/answering system. The authors chose RBMT because Bulgarian is a morphologically rich language. However, they do not mention which rule-based approach was used. Along with the RBMT, they used dictionaries and a PoS tagger in order to create rules which were then included in the SMT model akin to a *tree-based* approach. Consequently, the SMT system is the main part of their MT system. They used a parallel corpus as a gold standard dataset from EUROPARL²⁸ for evaluating their approach. Additionally, they used two WSD techniques which were supported by OntoWordNet and LT4eL [173]. Although they used LT4eL as a domain ontology, they suggested that DBpedia may be used to address other domains, because DBpedia fails in covering the information technology domain. LT4eL was included in OntoWordNet which is their previous work [174]. Thus, they were able to support WSD through the WordNet synsets inside Moses SMT system. The evaluation, comparing their hybrid MT system with the Moses system as baseline, showed no improvement for the BLEU metric. However, when the authors evaluated using the NIST metric, their system showed real improvement. The authors propose to generate more sophisticated rules for further improvements.

4.1.7. New perspective – Ontology-based MT

In this section, we describe two articles using SWT to translate contents without relying on well-known MT approaches. They present a MT system mainly based on SW methods.

- In the first work, Seo et al. [125] use an ontology created by themselves from a gold standard corpus by performing the ontology learning method [175]. This ontology is responsible for providing semantic knowledge of words. The syntactic analysis uses formal language expressed using Extended Backus–Naur Form (EBNF) notation [176] to match the English patterns defined beforehand. These patterns are only defined in the English Language, hence the MT system only translates contents from English to Korean. Their system is not able to perform a translation in both directions (round-trip translations). Co-occurring words in the corpus are represented by relationship properties in the ontology.

Thus, the algorithm performs WSD by analyzing the ontological relationships between parts of speech tags for

deciding the best translation. For instance, the Korean language is well-known to group meaning of several words together, like the Chinese language. Thus, when translating a given word, its meaning has to be determined. In the example they gave, they attributed the translation of “hard” to a given Korean character according to the part of speech given by the EBNF notation. Then, they were able to search for a translation of “hard” as an adverb having the meaning “with effort”. This method is comparable to a bag-of-words algorithm, but with additional graph features provided by the ontology to deal with Korean language structure.

- The second work by Shi et al. [123] proposes an ontology they also created. The ontology “SCIENTIST” describes terms in the physical science domain and was derived from other ontologies like SUMO. It is used to improve the semantic quality in their Chinese-English MT. The syntactic analysis part is done using Lexical Functional Grammar [177]. For the semantic analysis, their WSD is achieved by comparing relationship weighting between parts-of-speech of the words in the ontology, similar to the previous work.

Both articles show promising approaches. Even though these works are quite similar, the second is much more detailed and its concepts are more applicable in future works and for supporting other languages. Moreover, unlike the first, the second work is capable of making a round translation. Neither work includes an evaluation, and comparing their results directly is impossible due to their different domain ontologies. Consequently, they are not capable of translating content across contexts. Unfortunately, their source codes are also not publicly available.

4.2. Suggestions and Possible Directions

According to the surveyed papers, SWT have mostly been applied at the semantic analysis step, rather than at the other stages of the translation process due to their ability to deal with concepts behind the words and provide knowledge about them. Table 4 presents an overview of the surveyed papers, regarding each generic step of the MT approaches supported by SWT.

As SWT has developed, they have increasingly been able to resolve some of the open challenges of MT described in Section 3.5. They may be applied in different ways according to each MT approach. Although the potential graph structure contained in ontologies may act as a disambiguation method with high decision power, some SW concepts, such as the alignment of multilingual ontologies and the linking among monolingual knowledge bases, [178, 179] still need to be improved before SWT can be applied successfully in MT systems.

Additionally, the SW community has worked out basic suggestions for generating structured data. However, there are no well-defined rules for building the KBs, only common best practices according to Zaveri et al. [180]. Due to this lack of defined standards, some research works have produced erroneous ontologies or knowledge graphs into LOD repositories. Common issues include the following mistakes:

²⁸<http://www.statmt.org/europarl/>

Table 4: Semantic Web technologies in Machine Translation steps

MT approaches	MT Architecture					
	Analysis			Generation		
	Morphological	Syntactic	Semantic	Morphological	Syntactic	Semantic
Direct	X			X		
Transfer-based		X			X	X
Interlingua		X	X		X	X
Statistical			X			X
Example-based	X		X			X
Hybrid	X	X	X	X		

- Lack of well-defined object properties, e.g., cardinality or reflexiveness.
- Mixing of concepts among thesaurus, vocabulary, and ontology.
- Incorrect domain and range definitions.
- Use of ambiguous annotations.

Therefore, applying SWT to MT may seem difficult. However, recently some efforts from the Linguistic Linked Open Data (LLOD)²⁹ community have been directed to modeling linguistic phenomena, linguistic rules and translations in LOD [181].

In the following subsections, we discuss and suggest future potential solutions to MT challenges by applying SWT. From our point of view, SWT mostly contribute to addressing syntactic and semantic ambiguity problems in MT systems. Thus, we divide our suggestions into four categories according to their respective problem.

4.2.1. Disambiguation

Human language is very ambiguous. Several words have multiple interpretations depending on the context in which they are mentioned. In the MT field, WSD techniques are concerned with finding the respective meaning and correct translation to these ambiguous words in target languages. This ambiguity problem was identified early in MT development. According to Bar-Hillel [6], an MT system is not able to find the right meaning without a specific knowledge base. Although the ambiguity problem has been lessened significantly since the contribution of Carpuat and subsequent works [182–184], this problem still remains a challenge. As seen in Section 3, MT systems still try to resolve this problem by using domain specific language models to prefer domain specific expressions, but when translating a highly ambiguous sentence or a short text which covers multiple domains, the languages models are not enough.

According to surveyed articles, SW has already shown its capability for semantic disambiguation of polysemous and homonymous words. However, SWT were applied in two ways for supporting the semantic disambiguation in MT. First, the ambiguous words were recognized in the source text before carrying out the translation, applying a pre-editing technique. Second, SWT were applied to the output translation in the target

language as a post-editing technique. Although applying one of these techniques has increased the quality of a translation, both techniques are tedious to implement when they have to translate common words instead of named entities, then be applied several times to achieve a successful translation. The real benefit of SW comes from its capacity to provide unseen knowledge about emergent data, which appears every day. Therefore, we suggest performing the topic-modelling technique over the source text to provide a necessary context before translation. Instead of applying the topic-modeling over the entire text, we would follow the principle of communication (i.e from 3 to 5 sentences for describing an idea[185]) and define a context for each piece of text. Thus, at the execution of a translation model in a given SMT, we would focus on every word which may be a homonymous or polysemous word. For every word which has more than one translation, a SPARQL query would be required to find the best combination in the current context. Thus, at the translation table, the disambiguation algorithm could search for an appropriate word using different SW resources, such as BabelNet and DBpedia, in consideration of the context provided by the topic modelling. The goal is to exploit the use of more than one SW resource at once for improving the translation of ambiguous terms. The use of two or more SW resources simultaneously has not yet been investigated.

On the other hand, there is also a syntactic disambiguation problem which as yet lacks good solutions. For instance, the English language contains irregular verbs like “set” or “put”. Depending on the structure of a sentence, it is not possible to recognize their verbal tense, e.g., present or past tense. Even statistical approaches trained on huge corpora may fail to find the exact meaning of some words due to the structure of the language. Although this challenge has successfully been dealt with since NMT was presented between European languages [186], implementations of NMT for some non-European languages have not been fully exploited (e.g., Brazilian Portuguese, Latin-America Spanish, Hindu) due to the lack of large bilingual data sets on the Web to be trained on. Thus, we suggest gathering relationships among properties within an ontology by using the reasoning technique for handling this issue. For instance, the sentence “Anna usually put her notebook on the table for studying” may be annotated using a certain vocabulary and represented by triples. Thus, the verb “put”, which is represented by a predicate that groups essential information about the verbal tense, may support the generation step of a given MT system. This sentence usually fails when translated to rich morpholog-

²⁹<http://linguistics.okfn.org/>

ical languages, such as Brazilian-Portuguese and Arabic, for which the verb influences the translation of “usually” to the past tense. In this case, a reasoning technique may support the problem of finding a certain rule behind relationships between source and target texts in the alignment phase (training phase).

Reasoning techniques have been identified as a possible future way of supporting MT tasks because some remaining MT issues cannot be solved with explicit knowledge only. For instance, in accordance with Manning [187], some syntactic ambiguity gaps need to be addressed by human knowledge. This kind of human knowledge can be gained using reasoning over ontological relations which are described by humans. For example, in 2004 Legrand and Pulido [188] combined ontological knowledge with neural algorithms for performing the WSD task. The result was very promising, but unfortunately the work was discontinued. Additionally, some researchers, including Harriehausen-Mühlbauer and Heuss and Seo et al. [125, 129], have used reasoners to disambiguate words in MT systems.

For a given reasoning technique to be required, some previous steps need to be addressed. Currently, the Ontology-Lexica Community Group³⁰ at W3C has combined efforts to represent lexical entries, with their linguistic information, in ontologies across languages. Modeling different languages using the same model may provide an alignment between the languages, where it is possible to infer new rules using the language dependency graph structure and visualize a similarity among languages³¹. SW tools which perform reasoning and infer unseen concepts are called Reasoners. Examples include Pellet, RACER, FACT++, and DL-Learner [189]. For the sake of clarification, DL-Learner [190] would learn concepts about a specific source or target text modeled by Ontolex. Thus, DL-Learner could infer new facts across related languages.

Moreover, there are plenty of other ontologies and vocabularies which may support the description of languages, such as Olia [191], Lemon [192], GOLD [193] and NIF [194]. However, the aforementioned ontology issues may limit reasoner in its ability to support translations. Besides this drawback, a well-known problem of reasoners is the poor run-time performance, it has been the main problem for applying reasoning techniques over scientific problems. Therefore, they are not suitable for real-time MT approaches at this point in time. Furthermore, both deficiencies need to be addressed or minimized before implementing reasoners successfully into MT systems.

4.2.2. Named Entities

Most Named Entity Recognition and Disambiguation (NERD) approaches link recognized entities with database entries or websites [168]. This method helps to categorize and summarize text, but also contributes to the disambiguation of words in texts. The primary issue in MT systems is caused by common words from a source language that are used as proper nouns in

a target language. For instance, the word “Kiwi” is a family name in New Zealand which comes from the Māori culture, but it also can be a fruit, a bird, or a computer program. Named Entities are a common and difficult problem in both MT (see Koehn [4]) and SW fields. The SW achieved important advances in NERD using structured data and semantic annotations, e.g., by adding an `rdf:type` statement which identifies whether a certain kiwi is a fruit [195, 196]. In MT systems, however, this problem is directly related to the ambiguity problem and therefore has to be resolved in that wider context.

Although MT systems include good recognition methods, NERD techniques still need improvement. When a MT system does not recognize an entity the translation output often has poor quality, immediately deteriorating the target text readability. Therefore, we suggest recognizing such entities before the translation process and first linking them to a reference knowledge base. Afterwards, the type of entities would be agglutinated along with their labels and their translations from a reference knowledge base. For instance, in NMT, the idea is to include in the training set for the aforementioned word “Kiwi”, “Kiwi.animal.link, Kiwi.person.link, Kiwi.food.link” then finally to align them with the translations in the target text. In SMT, the additional information would be included by Extensible Markup Language (XML) Markup or by an additional model. This method would also contribute to OOV mistakes regarding names. This idea is akin to [139] where the authors encoded the types of entities along with the words to improve the translation of sentences between Chinese-English.

Another potential solution could apply type extraction or co-occurrence techniques and combine them with NERD methods. The solution would identify which pronouns (e.g., “it”) are related to entities that have already been mentioned in previous sentences. This would also improve the fluency of target texts. In addition to our suggestions, the contextual linking over texts can help users to acquire a deeper understanding of the translated content (as NERITS has done). Plenty of SW tools would be able to support this approach in accordance with Gangemi [197]. This work provides a complete comparison of SW tools, detailing their powerful capabilities for extracting knowledge.

4.2.3. Non-standard speech

The non-standard language problem is a rather important one in the MT field. Many people use the colloquial form to speak and write to each other on social networks. Thus, when MT systems are applied in dialogue systems, the input text frequently contains slang, Multiword Expressions (MWE), and unreasonable abbreviations. Additionally, idioms contribute to this problem, decreasing the translation quality. Idioms often have an entirely different meaning than their separated word meanings. Consequently, most translation outputs of such expressions contain errors.

For a good translation, the MT system needs to recognize such slang and try to map it to the target language. Some SMT systems like Google or Bing have recognition patterns over non-standard speech from old translations through the Web

³⁰<https://www.w3.org/community/ontolex/>

³¹This insight is already supported by a recent publication in Cicling conference <https://www.cicling.org/2017/posters.html> named “The Fix-point of Dependency Graph – A Case Study of Chinese-German Similarity” by Tiansi Dong et al.

using SMT approaches. In rare cases SMT can solve this problem, but considering that new idiomatic expressions appear every day and most of them are isolated sentences, this challenge still remains open. Moreover, each person has their own speaking form.

Therefore, we suggest that user characteristics can be applied as context for solving the non-standard language problem. These characteristics can be extracted from social media or user logs and stored as user properties using SWT, e.g., FOAF or SIOC [198] vocabularies. These ontologies have properties which would help identify the birth place or the interests of a given user. For instance, the properties *foaf:interest* and *sio:topic* can be used to describe a given person’s topics of interest. If the person is a computer scientist and the model contains topics such as “Information Technology” and “Sports”, the SPARQL queries would search for terms inserted in this context which are ambiguous. Furthermore, the property *foaf:based_near* may support the problem of idioms. Assuming that a user is located in a certain part of Russia and he is reading an English web page which contains some idioms, this property may be used to gather appropriate translations of idioms from English to Russian using a given RDF KB [199]. Therefore, a MT system can be adapted to a user by using specific data about him in RDF along with given KBs.

4.3. Translating KBs

According to the surveyed articles, it is clear that SWT may be used for translating KBs in order to be applied in MT systems. For instance, some contents provided by the German Wikipedia version are not contained in the Portuguese one. Therefore, the semantic structure (i.e., triples) provided by DBpedia versions of these respective Wikipedia versions would be able to help translate from German to Portuguese. For example, the terms contained in triples would be translated to a given target language using a dictionary containing domain words. This dictionary may be acquired in two different ways. First, by performing localisation, as in the works by J. P. McCrae [200] and Arcan [201, 202] which translates the terms contained in a monolingual ontology, thus generating a bilingual ontology. Second, by creating embeddings of both DBpedia versions in order to determine the similarity between entities through their vectors. This insight is supported by some recent works, such as Ristoski et al. [203], which creates bilingual embeddings using RDF based on Word2vec [204] algorithms, and Muhao Chen et al. [205], which generates multilingual knowledge graph embeddings for aligning entities across languages. Therefore, we suggest investigating a MT approach mainly based on SWT using NN for translating KBs. Once the KB are translated, we suggest including them into the language models for improving the translation of entities.

Besides C. Shi et al [139], one of the recent attempts to this direction was carried out by Arčan and Buitelaar [206]³² by

which the authors aimed at translating domain-specific expressions represented by English KBs in order to make the knowledge accessible for other languages. They claimed that KBs are mostly in English therefore they can not contribute to the problem of MT to other languages. Thus, they translated two KBs which belong to medical and financial domains along with the English Wikipedia to German. Once translated, the KBs were used as external resources in the translation of German-English. For the sake of brevity, they evaluated their approach in Phrase-based and NMT systems. The results were quite appealing then the investigation of this type of research requires to be fully exploited.

5. Conclusions and Future Work

In this paper, we detailed a systematic literature review of MT using SWT for translating natural language sentences. The review aimed to answer the four research questions defined in Section 2 by a thorough analysis of the 21 most relevant papers.

Our goal was to provide a clear understanding of how SWT have helped the translation process within MT systems. Few studies have been found, suggesting that this method is still in its infancy. The surveyed articles demonstrate that SWT have been mainly used for the disambiguation task in MT systems and their capabilities have steadily increased. Considering the decision power of SWT, they can not be ignored by future MT systems.

Nevertheless, there are still significant drawbacks. Although the research works provide strong evidence of general SW advantages in the translation process measured by automatic evaluation metrics. The real semantic contributions were assessed manually and the evaluators could measure improvement according to the respective domains through which the work was approached. BLEU was the automatic evaluation metric basically used by all research works and it lacks semantic measurement. Thus, decreasing the real contribution of SW in MT. Recent works on MT evaluation have shown promising advances for dealing with semantics in related metrics. These recent works [207, 208] attached SWT, in this case DBnary [209], to METEOR to handle meanings for non-English languages. In addition, MEANT has become the state-of-the-art in terms of evaluating semantics correlations in translated texts. Therefore, we expect that upcoming research works attempting to combine SWT with MT will be better evaluated by using these referred semantic metrics.

How can SWT enhance MT quality? Regarding this main research question, we identified that both semantic and syntactic disambiguation including entities, structural divergence and OOV words problems can all be tackled with SWT. Additionally, SWT and MT approaches face the problem of languages to be inherently ambiguous, in terms of lexicon, syntax, semantics and pragmatics. Identifying concepts in a KB or finding the right translation for a word are instances of the same WSD problem. Therefore, a deeper understanding of how pieces of information obtained from ontologies and KB on the one hand, and parallel and monolingual corpora on the other hand may contribute to solve these problems of ambiguity in MT. The

³²This paper was not included in this survey, because it was not peer-reviewed yet.

two most recently surveyed articles, [139, 140], which have implemented a translation model relying on structured knowledge, support our conclusion. They showed promising results even using an automatic evaluation metric, which does not consider semantics. Therefore, this work increases the evidence that SWT can significantly enhance the quality of MT systems.

Furthermore, we answered the first sub-question RQ1 by listing and discussing all surveyed articles. RQ2 is summarized in Table 3 where we list all applied SW methods and respective SW resources. For RQ3, in Section 4 we also discussed the impact of applying an ontology to MT. We conclude that ontological knowledge is generally beneficial for certain translation quality issues, mostly related to disambiguation in morphologically rich languages and sign languages. The ontological knowledge was a crucial resource for improving the translation between sign and spoken natural languages. We sought to answer RQ4, about the availability of SW-tools, and we could perceive that most of them were discontinued. Only AGDISTIS [195, 210], DBpedia Spotlight[171] and Babelify[211], which had supported some of the surveyed articles, are currently available. Moreover, we noticed that these SW tools performed only a specific task - disambiguation, for supporting the translations. Apart from the tools, BabelNet and DBpedia were used as KBs by almost of all surveyed works.

As a next step, we intend to elaborate a novel MT approach based on our suggestions made in Section 4, which means an approach capable of gathering knowledge from different SW resources simultaneously for addressing the ambiguity of named entities which can also alleviate the problem of OOV words. This insight relies on recent works[212, 213] which have guided the usage of external knowledge in NMT systems for overcoming the vocabulary limitation of NN models. Also, we aim at creating a method to structure natural language sentences into triples for supporting the generation task.

Future works that can be expected from fellow researchers, based on statements in their own papers, include the creation of linguistic ontologies describing the syntax of rich morphologically languages for supporting MT approaches. In addition, alignment between ontologies is expected to try to bridge gaps which are not addressed by the current SMT models. Well-known bilingual dictionaries have been mapped to RDF, then the creation of multilingual dictionaries have become easier for content translation. These RDF dictionaries can help to improve MT steps, such as alignment, or even translate, based entirely on such semantic resources.

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