Semantic Web based Machine Translation

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Abstract

This paper describes the experimental combination of traditional Natural Language Processing (NLP) technology with the Semantic Web building stack in order to extend the expert knowledge required for a Machine Translation (MT) task. Therefore, we first give a short introduction in the state of the art of MT and the Semantic Web and discuss the problem of disambiguation being one of the common challenges in MT which can only be solved using world knowledge during the disambiguation process. In the following, we construct a sample sentence which demonstrates the need for world knowledge and design a prototypical program as a successful solution for the outlined translation problem. We conclude with a critical view on the developed approach.

1 Introduction

Over the past decades, Machine Translation (MT) has undergone various changes with regard to the underlying technology. Starting in the middle of the last century with rule-based MT, a first logical step was taken towards the end of the century, when statistical methods in Natural Language Processing (NLP) gained overall importance, as the growing number of online available texts could be used as a basis for statistical computations performed on these texts and translations, which resulted in an enhancement of existing rules, statistics and thus results. The new field of Statistical Machine Translation (SMT) was born and MT systems became increasingly better as more and more texts and translations were available. In parallel to the developments in MT, the Web has significantly grown and gained importance, especially in the recently defined field of the Semantic Web. After having accepted statistical methods as a promising change in MT, we believe that a next logical step will combine MT with Semantic Web technology, resulting in a new focus which can be called Semantic Web Machine Translation (SWMT).

In this paper, we will develop our ideas step by step and will demonstrate on a sample sentence including a lexical ambiguity that our approach does not involve a costly disambiguation process on the basis of parsing online-dictionaries. Instead, we believe that modern Information Technology (IT) is aligned and committed to information and its markup, as the W3C Semantic Web technology stack[1] demonstrates, and that we can use the contained knowledge in our disambiguation process without additional MT rules or statistics being applied.

2 Development and change of focus in MT : from the rule-based past to the web-based future of MT

Traditionally, most MT systems were rule-based systems built on electronic analysis and generation grammars as well as a language-pair-dependent transfer component . These Rule-based Machine Translation (RBMT) systems always involved a careful and time-consuming development of grammatical rules.

More recent development in MT has started to use the vast amount of texts and knowledge that is available online for translations based on statistics

[1] http://semanticweb.org/wiki/Main_Page (URL last access 2011-12-18).

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and probabilities, leading to a separate focus in MT, namely SMT.

With the growing size of texts available in the web, it is a logical next step to consider using the available knowledge in these texts to enhance NLP applications, including MT, leading to a yet new focus, which we call SWMT.

In this chapter we will develop our idea by starting with a look at how MT has developed over the past decades, how it has made use of the expanding Web in recent years and where we see further potential in using existing knowledge for MT technology.

2.1 Statistical Machine Translation

The dream of automatically translating documents from foreign languages into English, or between any two languages, is one of the oldest pursuits of NLP, being a subfield of artificial intelligence research. Traditional MT systems computed translations primarily on the basis of analysis and generation phrase-structure-rules, which had to be manually coded in a costly fashion.

One of the leading users of SMT is Google and Google Translate engineer Anton Andryeyev, who explains SMT's essence as follows:

"SMT generates translations based on patterns found in large amounts of text. [...] Instead of trying to teach the machine all the rules of a language, SMT effectively lets computers discover the rules for themselves. It works by analysing millions of documents that have already been translated by humans [...].

[...] Key to SMT are the translation dictionaries, patterns and rules that the program develops. It does this by creating many different possible rules based on the previously translated documents and then ranking them probabilistically. Google admits this approach to translation inevitably depends on the amount of texts available in particular languages [...]." (Boothroyd 2011)

Therefore, with the change of available resources and the growing number of natural language that is available in machine-readable format as well as the growing number of users inputting corrections to machine translations manually, thus allowing a direct and correct match between source and target texts, we have entered this subfield of MT which focuses on a statistical analysis of texts, in which documents are translated according to a probability distribution $p(e|f)$ which states that a string e in the target language is the translation of a string f in the source language.

Philipp Koehn, being among the most popular SMT researchers and developers, also highlights today's quality of SMT and the relevance of the vast amounts of texts in the web, which provide the basis for SMT translations, by stating "Now, armed with vast amounts of example translations and powerful computers, we can witness significant progress toward achieving that dream." (Koehn et al. 2012)

The research field of statistical machine translation is a rather new field. In his commented bibliography[2] Koehn includes statistics about the distribution of publications in the SMT field across the years 1953 until 2008. It is clearly shown that only a few publications appeared before the millennium change and that SMT clearly became an issue of growing interest in the new millennium, with a peak in 2006. Scientists working in the MT field suddenly became aware of the relevance and potential provided by statistics in machine translation and computational linguistics in general. Still in 2003, Knight & Koehn stated, that "the currently best performing statistical machine translation systems are still crawling at the bottom", (Knight & Koehn 2004, p. 10), implying that most of the approaches hadn't gone beyond simple word to word translations yet and hadn't included more advanced stages of NLP, like syntax or even semantics. Among those who made essential contributions to the field of SMT was Kevin Knight who stated in 1999 that "We want to automatically analyse existing human sentence translations, with an eye toward building general translation rules we will use these rules to translate new texts automatically." (Knight 1999)

The previous statements all point at the vast knowledge included in the just as vast amounts of texts available in digital form in the internet, partly in the form of human sentence translations.

At the same time that MT started clearly moving into using the Web to search for machine-readable texts and translations that could be used in the expanding SMT field, Tim Berners-Lee (Berners-Lee & Hendler 2001) defined the knowledge, that is included in the Web content, to ex-

[2] `http://www.statmt.org/book/bibliography/` (URL last access 2012-01-30).

pand the traditional WWW to become a Semantic Web

As we are looking at an expanded view of how to use the Web, and specifically the Semantic Web, for our approach of MT, we would like to draw parallels between what has been said so far about MT and the innovative possibilities that the Semantic Web provides for MT research.

2.2 W3C Semantic Web

The World Wide Web (WWW) was once designed to be as simple, as decentralized and as interoperable as possible (Berners-Lee 1999, 36f.). The Web evolved and became a huge success, however, information was limited to humans. In order to make information available to machines, an extending and complementary set of technologies was introduced in the new millennium by the W3C, the Semantic Web[3] (Berners-Lee & Hendler 2001).

The base technology of the Semantic Web is the data format Resource Description Framework (RDF). Aligned to the so called AAA slogan that "Anyone can say Anything about Any topic" (Allemang & Hendler 2008, p. 35), it defines a structure that is meant to "be a natural way to describe the vast majority of the data processed by machines" (Berners-Lee & Hendler 2001). In addition to the AAA slogan, a basic construction paradigms of the Semantic Web is the Open World Assumption - the fact that there is always more knowledge than we currently know; new knowledge can always be added later.

RDF expresses meaning by encoding it in sets of triples (Berners-Lee & Hendler 2001), composed of subject, predicate and object, which are, in the N3-notation format[4], likewise written down as triples:

```
:subject :predicate :object
```

We see strong connections between MT and the W3C Semantic Web.

A lot of ideas exist on how to augment the Resource Description Framework (RDF) - the base format of the Semantic Web - with natural language. Since the beginning, RDF itself provided capacities for a "human-readable version of a resource's name" (Guha 2004), `rdfs:label`, with an optional language notation following RFC-3066[5] (Klyne & Carroll 2004). In addition to that, the Simple Knowledge Organization System (SKOS) ontology features a small selection of unicode labels for "creating human-readable representations of a knowledge organization system", `skos:prefLabel`, `skos:altLabel` and `skos:hiddenLabel` - but also remarks that it "does not necessarily indicate best practice for the provision of labels with different language tags" (Miles 2008).

Some alternatives developed to the approches above, to address limitations especially of `rdfs:label` and to represent natural language within semantic knowledge in a more sophisticated way, like the SKOS eXtension for Labels (SKOS-XL)[6], Lemon[7] and LexInfo[8].

And even in the area of wordnets, which might be considered as a more traditional NLP domain, W3C Semantic Web technology plays a role, as approaches were developed to bridge the gap between natural language representations within these wordnets and the design principles of the Semantic Web (Graves & Gutierrez 2005). The conversion of Princeton WordNet[9], for example, to RDF/OWL is covered by a W3C Working Draft (van Assem et al. 2006) or the GermaNet wordnet[10] equivalent approach (Kunze & Lüngen 2007), adapting the ideas of the Princeton WordNet conversation.

We decided to give a brief overview of the state-of-the-art of SMT and the Semantic Web, as both areas of research are not only very new developments but they share using information in the Web for their applications and they both offer promising enhancements to traditional, rule-based MT technology. Nevertheless, SMT and Semantic Web Technologies have fundamental differ-

[3] `http://www.w3.org/standards/semanticweb/` (URL last access 2012-01-25).

[4] `http://www.w3.org/DesignIssues/Notation3.html` (URL last access 2012-01-29).

[5] `http://www.ietf.org/rfc/rfc3066.txt` (URL last access 2012-01-25).

[6] `http://www.w3.org/TR/skos-reference/skos-xl.html` (URL last access 2012-01-26).

[7] `http://www.w3.org/International/multilingualweb/madrid/slides/declerck.pdf` (URL last access 2012-01-31).

[8] `http://lexinfo.net/` (URL last access 2012-01-31).

[9] `http://wordnet.princeton.edu/` (URL last access 2012-01-26).

[10] `http://www.sfs.uni-tuebingen.de/lsd/` (URL last access 2012-01-26).

ences in that SMT, with systems like Moses[11], Babel Fish or Google compute their translations on a pure probability count of n-grams of different length in order to find the best translation by picking the one that gives the highest probability. As these systems have access to a growing text corpus, which is, as in the case of Moses, directly enhanced by collecting manual corrections given by users after the system has computed an inadequate translation, they become better with time. But exactly these statistically based computations are neither possible nor allowed in the Semantic Web because of the Open World Assumption.

3 New idea: Enhancing NLP with Semantic Web technology

With our new approach, we suggest to base MT on a newly defined set of rules, which differ both from rules known from earlier MT approaches but also from any rules that are applied in SMT. Our rules follow Tim Berners-Lees vision, in that knowledge, once defined and formalized, is accessible in arbitrary ways. As mentioned earlier, we believe that modern IT follows the commitment of information and it's markup, and the Semantic Web technology stack is a perfect implementation of that paradigm.

To demonstrate our approach, we selected a common and well known issue: The problem in many areas of NLP is the ambiguity of natural language on various levels, from word level to sentence level. In many cases, strings can only be disambiguated on the basis of world or expert knowledge. How else would a machine decide on whether the prepositional phase is modifying the verb or the preceding noun in "He eats fish with a fork." vs. "He eats fish with bones."? Especially with translations, it is often crucial to understand the source text correctly, as otherwise ambiguities may result in incomprehensible target language translations, as the examples below will demonstrate.

The state of the art technology of the World Wide Web to express information, facts and relations for both humans and machines is RDF. So it is not unlikely that nowadays expert knowledge is encoded in that format, too.

Taking care of lacking expert knowledge with Semantic Web technology and thus extending existing MT technology seems to be a promising research area. Instead of just combining RBMT with SMT, we suggest to add the power of the Semantic Web to these existing technologies, as the previous approaches were not able to extract and use knowledge from the Web in their translation algorithms and thus leave ambiguities unsolved.

The previously quoted statements made it clear that MT can only be enhanced on the basis of a growing size of text. We claim that the next logical step is to use this growing size of text not only statistically, but in a well-defined way which is offered by Semantic Web technology. The power of our idea is the combination of a strong, proven technology with a popular, open, machine-readable data format.

In order to demonstrate how our approach will enhance existing MT systems, we chose to use a variety of MT systems, some rule-based (e.g. PT[12]), other statistic-based (e.g. Babel Fish, Google, and Moses) to compare their context-free translation results against our approach. We use those context-free translation results as a starting point for further processing with Semantic Web technology. Traditional MT technology should therefore not be replaced, but enhanced with semantics, to benefit from the advantages provided by the Web.

In our sample scenario, the required world knowledge for the sample sentence `Pages by Apple is better than Word by MS.` is modelled as RDF instances. We selected a simple file-based storage, with the actual translations being stored as `rdfs:labels`[13] which are localized as defined in Best Common Practice 47[14] (BCP47). To take advantage of the powerful Semantic Web tool set, parts of the world knowledge are not directly defined, but can be inferenced by Web Ontology Language (OWL) capacities. The goal is to produce a semantically good translation for the given sentence.

[11]Moses is a statistical machine translation system developed by the Statistical MT Research group of University of Edinburgh, `http://www.statmt.org/moses/`.

[12]Personal Translator 14 distributed by Linguatec.

[13]`http://www.w3.org/TR/rdf-schema/##ch_label` (URL last access 2011-12-19).

[14]`http://www.rfc-editor.org/rfc/bcp/bcp47.txt` (URL last access 2011-12-19).

3.1 A sample scenario

The first step is the construction of an expressive sample scenario where world knowledge is critical for the MT. We looked at the results a number of different translation tools computed for our sample sentence: Google Translator[15], Bing Translator[16], an online demo of Philipp Koehn's Moses[17], Linguatec Personal Translator PT 14[18] (rule-based) and the reference translation in this paper, Yahoo! Babel Fish[19].

Research concluded with the following sentence, requiring the "expert knowledge" that a vendor called `Apple` produced a product named `Pages` and a vendor called `MS` (very popular shortform of `Microsoft`) a product named `Word`:

```
Pages by Apple is better
than Word by MS.
```

One important measure to stress the translation service is to use "indirect" product names (`Pages by Apple` and **not** `Apple Pages`) to prevent them from deriving product names from possible dictionary entries. Another "trap" was to abbreviate `Microsoft` with `MS` to irritate possible n-gram-statistics.

The resulting German translations of the sample sentence were the following:

Google Translator:

```
Pages von Apple ist besser
als Word MS.
```

Bing Translator:

```
Seiten von Apple ist besser
als MS Word.
```

Babel Fish:

```
Seiten durch Apple ist besser
als Wort durch Frau.
```

Moses Machine Translation Demo:

```
Seiten von Apple ist besser
als Word von MS behandelt.
```

Personal Translator PT 14

```
Paginiert von Apple ist
besser als durch MS
auszudrücken.
```

All translations failed, because they did not take semantic relations into consideration. This is a systematic issue in MT, demonstrating the necessity of including world knowledge in the computation of the target translation.

4 More examples

As ambiguities are a common MT problem, there are various examples where MT can be enhanced by world knowledge.

Consider, for example, popular persons that have ambiguous last names - like the politicians George W. Bush, Helmut Kohl[20], Joschka Fischer[21] to name a few. MT systems are likely to translate those names if they are not included in dedicated expert dictionaries. But thanks to projects like DBpedia[22], we already have the knowledge available in a Semantic Web accessible format and could just use it.

Another area that might benefit from a Semantic Web Machine Translation is the internationalization of technical documents or handbooks, which usual deal with several termini technici. Once modelled in RDF, the required expert knowledge is universally present and could aid the translation process as well.

5 Analysis

World knowledge is the crucial point for the translation quality of the selected sample sentences. It becomes obvious that in situations like this, with missing expert dictionaries, rule sets or lacking statistical tooling like N-grams, the translation quality is relatively low. And this is not an unrealistic scenario: There will always be uncovered areas in expert dictionaries or missing statistics in a certain domain.

In the given example, if we are looking at the Babel Fish translation, the translation engine was totally mousetrapped as it translated the `Apple` product `Pages` with the obviously context free,

[15] `http://translate.google.de/` (URL last access 2011-12-18).

[16] `http://www.microsofttranslator.com/` (URL last access 2011-12-18).

[17] `http://demo.statmt.org/index.php` (URL last access 2012-01-29).

[18] `http://www.linguatec.net/products/tr/pt` (URL last access 2012-01-29).

[19] `http://de.babelfish.yahoo.com/` (URL last access 2011-12-18).

[20] The proper name Kohl is also the German word for cabbage.

[21] Fischer means fisherman in German.

[22] `http://dbpedia.org/` (URL last access 2012-03-12).

German translation Seiten. Furthermore, it interpreted MS as salutation and Word as the German Wort - all mistakes made caused by lexical ambiguities because of the lack of context knowledge.

6 Implementation

In order to prove our idea, we have developed a prototypical application implementing a Semantic Web enhanced SMT. One principal design goal was to keep the program simple, but to apply state-of-the-art Semantic Web technology like RDF and the query language SPARQL, which are both W3C recommendations.

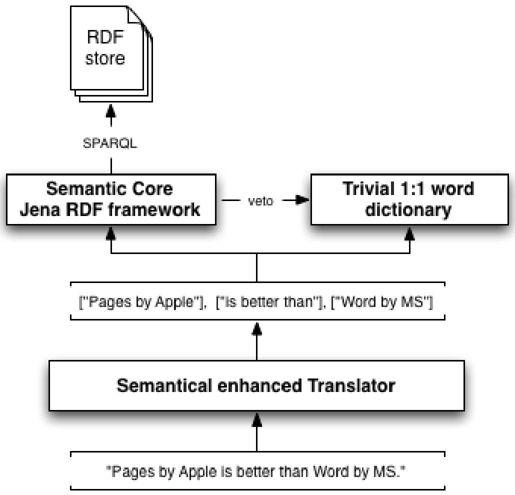

Figure 1: Architectural overview of the involved components and exchanged tokens.

And because of the powerful but easy to use Jena Semantic Web Framework[23], a prototype implementation is written in the Java programming language. The involved MT-components are:

Trivial word dictionary Performs a one-by-one word translation. Entries are designed to reflect the translation results of Babel Fish.

Semantic Core Reads a file based RDF triple store, executes SPARQL-queries and performs reasoning to inference new knowledge. Resulting text phrases may override certain results derived by dictionary entries.

The following sections give more details about the concrete implementation of those components and the overall execution logic.

[23] http://jena.sourceforge.net/ (URL last access 2011-12-19).

6.1 Trivial word dictionary

To fake Babel Fishs translation logic, a very simplified dictionary is defined with the content aligned at its online pendant. As figure 2 shows, the context free translation is reproduced with word-by-word translations.

English	German
Apple	Apfel
Pages	Seiten
Word	Wort
better	besser
...	...

Figure 2: Simplified dictionary to reproduce Babel Fishs simple and context free translation results.

6.2 Semantic Core

The much more interesting part is modelling the world knowledge with Semantic Web technologies. Thereby, a simple file based RDF store is used. The notation format is consistently N3[24], because of its very good human-readability.

As mentioned in previous sections, world knowledge about Apple and Microsoft is crucial in this translation task. So the first statements within the RDF store are about both vendors and the products they produce[25]:

```
:apple a :vendor, :trigger;
  rdfs:label "Apple";
  :produces :numbers , :pages ,
      :iphone .
```

In this case, the instance :apple is defined to be of the types :vendor and :trigger. While the former type has no special meaning in this context, the latter is especially important: :trigger-instances mark significant keywords, indicating that additional world knowledge should be loaded when they occur in a sentence. So in this example occurrence of the word Apple (rdfs:label of :apple) in the source text triggers loading and parsing of the :apple instance and all uses of it within the store.

Furthermore, some products are defined to be produced by :apple.

[24] http://en.wikipedia.org/wiki/Notation3 (URL last access 2011-12-19).

[25] For the sake of simplicity, all statements are aligned in the default namespace http://www.example.org/##.

The property `:produces` as well as its opposite `:producedBy` are defined as follows:

```
:produces rdfs:label "produces"@en-
    US, "produziert"@de-DE .
:producedby rdfs:label "by"@en-US, "
    von"@de-DE .
```

Note that both properties have dual-language-labels. This allows the program express the world knowledge `:apple :produces :iphone` in simple but natural English language as well as in German.

In the next step, both properties are semantically connected as `owl:inverseOf` each other:

```
:produces owl:inverseOf :producedby
```

This few statements already allow *inferencing* - reasoning about information that is given implicitly. So it is not only a fact that `:apple :produces :iphone`, but also after OWL-inferencing the fact that `:iphone :producedBy :apple` - without having to state that directly.

Finally, the products get their proper names assigned:

```
:numbers rdfs:label "Numbers" .
:word rdfs:label "Word" .
:windows rdfs:label "Windows" .
:pages rdfs:label "Pages" .
```

This few lines form the knowledge base which is, thanks to inferencing, sufficient to solve the translation task. The following dictionary entries can directly be read out of the RDF knowledge base:

```
Microsoft produces Windows
MS        produces Windows
Microsoft produces Word
MS        produces Word
Apple produces Pages
Apple produces Numbers
```

By evaluating the predicates `:produces` and inferencing the `:producedBy` statements, the knowledge base in addition contains the inverted entries:

```
Word by MS
Word by Microsoft
Word produced by MS
Word produced by Microsoft
Windows by MS
Windows by Microsoft
Windows produced by MS
Windows produced by Microsoft
```

6.3 Wiring it together

As mentioned before, the Semantic World Knowledge should enhance traditional MT translations. Therefore, the program produces technically two translations of the sentence `Pages by Apple is better than Word by MS.`: The first translation is done by the trivial dictionary, simply by string-replacing English with German words according to figure 2. The second translation first tries to find a better translation by checking trigger keywords, querying the RDF store for a knowledge, inferencing relationships and resolving labels for the right language, before it continues with the same word-by-word-replacing mechanism like in the fist translation.

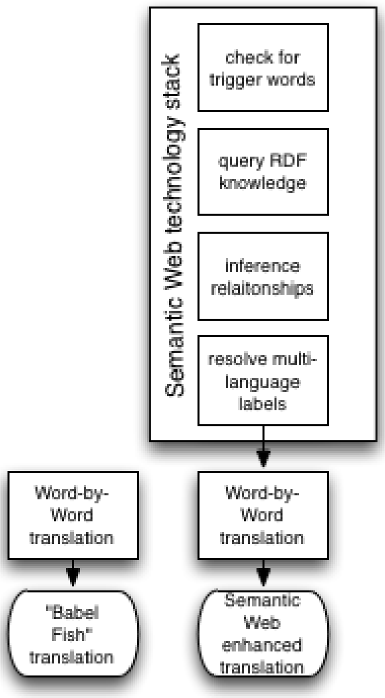

Figure 3: The two translations produced by the program and their technological foundation.

6.4 Program execution

Our prototype simply executes both described translations and print the result out.

```
Source sentence:
    Pages by Apple is better than
    Word by MS.

Semantic Web enhanced translation:
    Pages von Apple ist besser als
    Word von MS.
```

These simple lines, specially the "Semantic Web enhanced translation", involve a lot of processing in the background which is not visible to the user - except for his waiting time. However, a semantically correct translation solution was found.

7 Critical view on the solution

We feel we created something notable here. However, we stand at the very beginning of our research and have encountered corresponding issues.

Surprisingly, implementation of the program logic - especially the query mechanism - turned out to be quite complicated, even for a simple scenario like in this case with a very limited corpus. As a result, the stepwise refinement of a translation (trigger word, query of knowledge, inference relationships and multi-language-label resolution) consists of a lot SPARQL queries. These queries require some processing time and power, which is both already notable in this tiny example. This finally leads to the conclusion that performance might be a major withdraw of our approach, at least for the current implementation.

Another issue was connected to data format: the translation environment, especially the usage of RDF triples consisting of subject, predicate and object, might be regarded to be too much aligned at the very special and constructed problematic of only a number of realtime problems. Sentences have to be somehow split into triples, which is quite an artificial border - not to say a technical limitation - of RDF. Real world NLP surely does not fit into the tripartite simplifications of RDF, and the question is then how often real world problems would benefit from this solution.

Another issue is the Open World Assumption, built into each Semantic Web component: There is no golden standard truth in the Semantic Web and therefore we will never be able to find the "best" translation for a given sentence within SPARQL-queries or inferencing results. Probably, our approach does not hold for providing complete translation solutions, but for giving very qualified suggestions. Some SMT tools, like Moses, actually do work with suggestions.

However, some of this issues might be solved by applying more sophisticated NLP / MT technology, like n-grams. Besides these issues, the program works as expected and Semantic Web technology was successfully used to integrate world knowledge into a MT process. Thus, the translation gathered a better quality and it thus can be stated that the experiment was successful.

8 Related work

The project Monnet has, according to its mission statement[26], a similar idea to combine MT with Semantic Web technology. However, results are still pending or not publically accessible at this point.

We also acknowledge the work by Elita and Birladeanu (2005), who outlined the combination of the Semantic Web with Example Based Machine Translation (EBMT), which is very much related to our approach. However, there are major differences: Elita and Birladeanu (2005) only applied their technique on certain phrases of offical documents - sequences of words they call "fields" (Elita & Birladeanu 2005, p. 14). Our idea is however to aid translation of complete sentences. Another very important difference is the intensiveness of use of W3C technology. Unlike Elita and Birladeanu (2005), we heavily use RDF, SPARQL and - probably the most promising matter of fact - OWL reasoning and try to follow the Semantic Web standard tooling very strictly.

9 Outlook

At this point in our research, we have not yet combined existing MT technology, especially SMT, with SWMT. The combination of approaches has yet to be explored, but existing MT technologies and SWMT are certainly not mutually exclusive and we suspect that a combination of MT approaches will lead to yet even better results, especially in cases where the translation quality is based on world or expert knowledge.

10 Conclusion

In the recent past, MT researchers have already discussed the combination of RBMT and SMT (Hutchins 2009, pp. 13-20). We suggest to add yet another possibility in MT to existing MT approaches, namely a Semantic Web based MT (SWMT).

[26] `http://www.monnet-project.eu/Monnet/Monnet/English?init=true` (URL last access 2012-01-26).

In this paper we have taken a next logical step in MT technology by including not only the vast amounts of texts available in the Web to enhance MT quality applying statistical computations across online texts and translations, but going one step further by looking at the power of and knowledge contained in the Semantic Web.

By taking advantage of the knowledge in the Web of the future, our approach of combining Semantic Web technology with MT allows this world knowledge to be made available for machine translations, thus enhancing challenges in MT, such as lexical ambiguities. In our discussed sample sentences, we have shown that a solution for the disambiguation would traditionally involve a costly disambiguation process or would be left unsolved. Using our SWMT approach, the MT quality benefits from world knowledge extracted from the Semantic Web and by its technology.

This combination of MT with Semantic Web technology results in a new focus of MT which we suggest to be called Semantic Web based MT (SWMT).

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