Combining Semantic and Syntactic Generalization in Example-Based Machine Translation

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Example-Based Machine Translation (EBMT): instance of Corpus-Based Machine Translation (CBMT), like SMT

- main difference between SMT and EBMT: type of knowledge that is consulted at runtime:
  - SMT systems consult probabilities of source language–target language (SL–TL) word or phrase pairs which they have learned from the training data offline
  - EBMT systems consult the training set (their example base) directly

- EBMT systems have often performed worse than SMT systems in the past
biggest shortcoming of EBMT: does not combine translations of phrases well (boundary friction)
particularly frequent when translating into a morphologically rich language (e.g., into German)

Example

sentence pairs in an example base, Way (2001):

A big dog *eats a lot of meat.* – Ein großer Hund *frisst viel Fleisch.*
I have *two ears.* – Ich habe *zwei Ohren.*

EBMT system might make use of phrases shown in bold to translate a sentence like *I have a big dog.* into Ich habe ein großer Hund. → would neglect the fact that German uses different inflectional forms to mark grammatical case: German phrase *ein großer Hund* is a nominative noun phrase, but *Ich habe* requires accusative object (*einen großen Hund*)
among the best-performing systems in EBMT: systems that make use of generalized templates

generalized templates: SL–TL pairs in which certain parts have been replaced by variables

provide an additional layer of abstraction and can prevent a system from having to revert to word-by-word translation

our experiments: combining two existing EBMT systems that rely on generalized templates → improvement over the individual performances of these two systems? → no, but improvements over a lexical EBMT system
Generalized Templates in EBMT II

- generalized templates: risk of overgeneralizing (replacing too many parts of an SL–TL pair with variables) → templates are usually restricted to certain categories of words
- semantic generalization: Kitamura and Matsumoto (1995)
- syntactic generalization: Güvenir and Tunc (1996), Kaji et al. (1992)
- generalization over sequences of words: Cicekli and Güvenir (2001)
two systems, both started out as purely lexical EBMT systems, i.e., did not make use of generalized templates extensions:

1. *Marclator*: generalization over function words
2. *CMU-EBMT*: semantic and syntactic generalization
EBMT at Dublin City University: *Marclator*

- developed at Dublin City University (DCU), part of the *MaTrEx* architecture (Stroppa and Way, 2006) ([http://www.openmatrex.org/marclator/marclator.html](http://www.openmatrex.org/marclator/marclator.html))
- modules: chunking, word alignment, chunk alignment, recombination
Chunking in *Marclator*

- system segments both the training and the test data into chunks
- chunking is based on the Marker Hypothesis (Green, 1979): psycholinguistic hypothesis stating that every language has a closed set of elements that are used to mark certain syntactic constructions
- set of elements includes function words and bound morphemes (-*ing* as an indicator of English progressive-tense verbs)
- *Marclator* chunking module solely considers function words as indicators of chunk boundaries
Chunking in *Marclator II*

- each function word (*Marker word*) triggers the opening of a new chunk, provided that the preceding chunk contains at least one non-Marker word

**Example**
e. g., *He was | on the bus*
# Chunking in *Marclator III*

| Category                     | Example       |
|------------------------------|---------------|
| determiner                   | *den*         |
| personal pronoun             | *euch*        |
| demonstrative pronoun        | *jenem*       |
| possessive pronoun           | *seine*       |
| interrogative pronoun        | *welch*       |
| indefinite pronoun           | *andere*      |
| relative pronoun             | *denen*       |
| preposition                  | *abseits*     |
| coordinative conjunction     | *aber*        |
| subordinative conjunction    | *falls*       |
| cardinal numeral             | *eins*        |
| numeric expression           | *neunundneunzig* |
| auxiliary/modal verb         | *darf*        |
| punctuation                  | *!*           |

**Table:** Sample Marker word for each category

- entries are included in their inflected forms
Word and chunk alignment in *Marclator*

- word alignment: *Giza++* (Och and Ney, 2003)
- chunk alignment: edit-distance-style algorithm in which distances are replaced by opposite-log conditional probabilities (Tinsley et al., 2008)
Recombination in *Marclator*

- left-to-right monotone recombinator
- translating:
  1. matching sentence
  2. if none is found: sentence is chunked
  3. each chunk that is not found in the example base is then split into single words

if several TL correspondences for an SL chunk or word are found in the example base, the one with the highest probability is chosen

output: single hypothesis for each input sentence
problem inherent in the approach described is that the chunks of an input sentence often cannot be found in the example base

goal: increase the chunk coverage of a system

Gough and Way (2003) extended a precursor to Marclator by including an additional layer of abstraction: produced generalized chunks by replacing the Marker word at the beginning of a chunk with the name of its category

Example

*of a marathon → <PREP> a marathon*
EBMT at Carnegie-Mellon University: *CMU-EBMT*

- *CMU-EBMT*: part of *PanLite* (Frederking and Brown, 1996), an MT architecture developed at Carnegie-Mellon University (CMU)
  
  [http://sourceforge.net/projects/cmu-ebmt/](http://sourceforge.net/projects/cmu-ebmt/)

- modules: matching, alignment, recombination
Matching and Alignment in *CMU-EBMT I*

- every substring of the input sentence with a minimum length of two tokens that appears in the SL half of the example base is extracted
- for each of these fragments, system identifies the smallest and the largest possible segment in the TL sentence that correspond to it (on the basis of bilingual dictionary and, optionally, a TL synonym list)
- every possible substring of the largest segment that contains at least the minimal segment receives a score
- alignment score is the weighted sum of the values of eight features, which include:
  - number of SL words with no correspondences in the TL segment
  - number of TL words with no correspondences in the SL fragment
  - number of SL words with a correspondence in the TL sentence but not in the relevant TL segment
  - difference in length between the SL and the TL segment
- translations are passed on to the recombination step as long as their scores do not exceed five times the length of the SL fragment
Generalized Templates in CMU-EBMT I

- Brown (1999): generate semantic and syntactic generalized templates (equivalence classes)
- class members can in turn contain classes

| Class           | Sample member                      |
|-----------------|------------------------------------|
| `<religion>`    | Christianity – Christentum         |
| `<month>`       | December – Dezember                |
| `<fullname-m>`  | `<firstname-m> <lastname> – <firstname-m> <lastname>` |
| `<fullname-m>`  | George Washington – George Washington |
| `<adj-s>`       | affordable – accesible             |
| `<noun-m-p>`    | painters – pintores                |
| `<np-m>`        | `<poss> <noun-m> – <poss> <noun-m>` |
| `<np-f>`        | `the <noun-f> – la <noun-f>`      |
| `<np-f>`        | `a <color> <noun-f> – une <noun-f> <color>` |

Table: Semantic and syntactic equivalence classes
Generalized Templates in *CMU-EBMT II*

- The system generalizes both the training and the test set: recursively replaces words and phrases that are part of an equivalence class with the corresponding class tag.
- Syntactic classes are applied before semantic classes.
- Training data: generalization is performed only if a member of a particular equivalence class is found in both the SL and the corresponding TL sentence.
Generalized Templates in *CMU-EBMT* III

- test set: all members of an equivalence class are replaced recursively
- matching process is equivalent to that of the purely lexical *CMU-EBMT* system, with the apparent difference that here, two matching levels – a lexical and a generalized one – exist
- alignment: proceeds in the same way as in *CMU-EBMT*
- following this, the rules that were stored during the generalization of the input sentence are applied in reverse so as to transform the generalized TL fragments into word form TL fragments
Our Approach I

- combining the generalized template extensions of *Marclator* and *CMU-EBMT* → build new system that applies both the DCU and the CMU generalization scheme

- goal: see whether our combined system could outperform the two individual systems → for this, we ran an experiment with the combined system as well as one with each individual system

- we (re-)implemented the three approaches on top of *Marclator*

- three systems:
  1. *Marclator* with DCU generalized templates (System 1)
  2. *Marclator* with CMU generalized templates (System 2)
  3. *Marclator* with DCU & CMU generalized templates (System 3)
Our Approach II

- experimental data set: English–German subtitles provided by a commercial subtitling company
- corpus contained 1,133,063 subtitles which consisted of on average 8.9 tokens for English and 7.9 for German
- training set: 1,130,717 subtitles
- test set, development set: 1,173 subtitles each
System 1: DCU Generalized Templates I

- includes the generalized template extension to Marclator
- if a chunk is not found in example base: replace the Marker word at the beginning of a chunk by its corresponding Marker tag and search for the resulting generalized chunk in the example base (if this attempt fails, the system reverts to word-by-word translation)
Example

an SL chunk *i ’ve finally got* cannot be found in the example base
→ System 1 generalizes it to <PERS_PRON> ’ve finally got
→ extracts the corresponding TL generalized chunk, e.g.,
  <PERS_PRON> haben
→ searches for a German translation for the SL Marker word *i* (underlying the SL Marker tag <PERS_PRON>) in the word alignments
→ finds, e.g., *ich*
→ produces the TL chunk *ich haben*

translation is deficient → discussion of problems inherent in the approach coming up
81 classes for language pair English–German provided to us by the developer of the CMU-EBMT generalized extension, majority are semantic classes

- classes contain a total of 5545 replacement rules (equivalence class tag and an SL–TL pair whose two halves may be replaced by the tag)
System 3: DCU & CMU Generalized Templates

- combines Systems 1 and 2 → generalizes over DCU Marker words as well as CMU semantic and syntactic equivalence classes
- DCU and the CMU generalization schemes are not mutually exclusive → overlaps, i.e., the CMU classes contain 50 words that are also Marker words for English (e.g., *after*, *and*, *before*), and 19 for German (e.g., *aber*, *allen*, *er*) → we prompted the system to generalize over the Marker words first, giving preference to the DCU scheme in case of overlaps
Baseline Systems

three baselines:

1. *Marclator* (non-generalized)

2. *OpenMaTrEx* (Dandapat et al., 2010): uses EBMT chunk pairs from *Marclator* and SMT phrase pairs from *Moses* default configuration (5-gram language model with modified Kneser-Ney smoothing, tuning via MERT, optional binary feature that records whether a phrase pair is an EBMT chunk pair or not)

3. *Moses* (Koehn et al., 2007): default system included in *OpenMaTrEx* (5-gram language model, modified Kneser-Ney smoothing, tuning via MERT (Och, 2003), lexicalized reordering model)

language models for *Moses* and *OpenMaTrEx*: TL side of training data
Results I

| System     | BLEU   | NIST   | METEOR |
|------------|--------|--------|--------|
| 1          | 0.1274 | 4.3948 | 0.4052 |
| 2          | 0.1269 | 4.3815 | 0.4047 |
| 3          | 0.1277 | 4.3937 | 0.4051 |
| Marclator  | 0.0995 | 4.2411 | 0.3990 |
| OpenMaTrEx | 0.2763 | 5.7880 | 0.4914 |
| Moses      | 0.2709 | 5.7472 | 0.4854 |

Table: Evaluation scores

- no agreement among all three metrics as to which system performed best: System 3 performed best according to BLEU, while System 1 performed best according to NIST and METEOR
our generalized EBMT systems achieved higher scores than the lexical EBMT system *Marclator* supports earlier findings according to which EBMT systems benefit from generalized templates

investigated the generalized chunk coverage of Systems 1 and 2 (number of successful generalized chunk matches with respect to the total number of attempts made at matching a generalized chunk): 8.26% for System 1, and 2.14% for System 2 (very low) → the higher generalized chunk coverage of System 1 was the reason why this system performed better than System 2
low generalized chunk coverage of System 2: demonstrates the problem inherent in the use of semantic word classes, which form the majority of the CMU equivalence classes → classes are very specific, many of them (e.g., *city*, *company*, *country*) have proper name members → on average, each class contains 69 members → to improve the generalized chunk coverage, number would have to be increased

combining Systems 1 and 2 into System 3 did not yield a clear improvement over the individual performances of these two systems → due to overlaps in the generalization schemes

System 1: one major source of errors: chunk-internal boundary friction
boundary friction is normally caused by combining two separate translation units that do not agree in grammatical case with the introduction of Marker-based templates, it can also take place *within* a single chunk, i.e., when a Marker word is inserted that does not agree with the grammatical properties of the rest of the chunk
in the case of translating from English to German, inserting TL Marker words context-insensitively (as is done in System 1) is error-prone: due to the morphological richness of German, an English Marker word can correspond to multiple word forms of the same lemma on the German side. e.g., English Marker word *are* can correspond to German Marker words *bist*, *sind* and *seid*

Example

*are you sure* . . . – *sind du sicher* . . .

chunk-internal boundary friction: combination of *sind* and *du* is grammatically incorrect
our EBMT systems performed much worse than the baseline systems *Moses* and *OpenMaTrEx* → performance gap is largely due to the recombination module of *Marclator* (monotone recombinator, outputs only the one-best hypothesis, no language model is applied) → both *OpenMaTrEx* and *Moses* apply a language model → it is essential for an EBMT system to make use of a language model for hypothesis recombination
Conclusion I

- experimented with combining two existing EBMT systems that rely on generalized templates → combined system did not yield a significant improvement in translation quality compared to the individual performances of the two systems
- however, the generalized EBMT systems consistently outperformed the lexical EBMT baseline → shows that generalized templates are beneficial to an EBMT system’s performance
- more difficult to achieve a high generalized chunk coverage with semantic generalized templates than with generalized templates based on function words
  semantic generalized templates have the advantage that they do not interfere with the grammar of a sentence
generalized templates based on function words are relatively easy to compile
system which relies on such templates can suffer from chunk-internal boundary friction
to reduce the chunk-internal boundary friction problem, we plan to develop an algorithm that context-sensitively instantiates TL Marker tags by using a language model → incorporate it into our generalized template extension of Marclator
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