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# Latest trends in hybrid machine translation and its applications<sup>☆</sup>

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## Abstract

This survey on hybrid machine translation (MT) is motivated by the fact that hybridization techniques have become popular as they attempt to combine the best characteristics of highly advanced pure rule or corpus-based MT approaches. Existing research typically covers either simple or more complex architectures guided by either rule or corpus-based approaches. The goal is to combine the best properties of each type.

This survey provides a detailed overview of the modification of the standard rule-based architecture to include statistical knowledge, the introduction of rules in corpus-based approaches, and the hybridization of approaches within this last single category. The principal aim here is to cover the leading research and progress in this field of MT and in several related applications.

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## 1. Introduction

Machine translation (MT) is the area of natural language processing (NLP) that focuses on obtaining a target language text from a source language text by means of automatic techniques. MT is a multidisciplinary field and the challenge has been approached from various points of view including linguistics and statistics. The existence of different perspectives has made possible the proliferation of hybrid methodologies. Hybrid methods focus on combining the best properties of two or more MT approaches. Nowadays, it has become very popular to include rules in statistical MT (SMT) approaches. However, there are also relevant works on enhancing standard rule-based MT (RBMT) by adding statistical knowledge. Recent initiatives such as the three editions of the HyTra workshop<sup>1</sup> show that linguists, engineers and computer scientists actively interact in the interests of building successful hybrid architectures, formulating proposals and conducting experiments.

This survey paper reviews recent methods that combine and hybridize MT approaches in single architectures, and thus, two closely related lines of research fall outside our scope. First, the methodologies of multi-engine combination,

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<sup>1</sup> <http://parles.upf.edu/llocs/plambert/hytra/hytra2014/>.

which have been widely studied in MT,<sup>2</sup> as well as in other related areas (e.g. speech recognition). These approaches assemble MT outputs, not MT architectures. And second, the integration of linguistic knowledge into SMT when studies do not consider different MT paradigms. For a survey on this specific topic see [Costa-jussà and Farrús \(2014\)](#).

The rest of the paper is organized as follows. Section 2 explains two classifications of MT approaches. Section 3 reports the main hybridization methods within and across paradigms. Section 4 describes several MT applications with hybrid components. Finally, Section 5 summarizes the main findings of this survey.

## 2. Classification of machine translation

Basically, MT approaches can be classified into different paradigms using two criteria: either *the level of representation* or *the sources of information*.

### 2.1. Level of representation

When classifying MT by level of representation, we can think of the Vauquois pyramid that basically contains: direct, transfer and interlingua approaches.

*Direct.* Approaches at the bottom of the Vauquois pyramid require one single step transformation between source and target, without analysis of the source language and without generation of the target language. Within this category, we might find simple dictionary-based translations.

*Transfer.* Approaches in the middle of the Vauquois pyramid consist of three steps: analysis, transfer and generation. This category includes RBMT, EBMT and SMT approaches.

*Interlingua.* Approaches at the top of the Vauquois pyramid consist of two steps: analysis and generation. The analysis transforms the source language into the interlingua representation and the generation transforms this interlingua representation into the target language. Interlingua is a universal representation of all languages, needing no transfer stage.

[Wu \(2005\)](#) offers observations as to whether a system can be considered direct or transfer depending largely on how much or how little language-specific monolingual analysis is carried out and also how close the intermediate representations are to the source and target texts themselves. Essentially, most of the approaches (other than interlingua) mentioned in this article could be classified as transfer-based engines, with varying degrees of complexity in their transfer, analysis and generation stages.

### 2.2. Sources of information

MT sources of information can be rules or data. The former is linguistically motivated, and the latter is more statistically motivated.

*Rules.* MT approaches based on rules (i.e. RBMT) use linguistic information such as monolingual and bilingual dictionaries combined with human linguistic knowledge. Rules are developed manually to transfer text in a source language text into a target language text. Most popular RBMT approaches apply three different phases: analysis, transfer and generation.

*Data.* Data-driven MT approaches use information from data and complex algorithms which together are capable of modeling translation. Data driven MT includes: example (EBMT) and statistical-based (SMT). By definition, EBMT approaches perform a direct translation by analogy and it can be seen as a pattern matching problem. Unlike these, SMT systems try to find the most probable translation given the source sentence, by reference to the models built using data such as the translation and language model ([Brown et al., 1993](#)). SMT can be classified into phrase, syntax and hierarchical. The main difference among these models is the structure of the bilingual units which can be built from: (1) plain text in the case of phrase models; (2) more complex data including grammars and dependency trees in syntax models; and (3) plain text but allowing hierarchical units in hierarchical systems.

Given that hybridization is the focus of this study, we will consider this latter criterion (sources of information) in order to distinguish MT paradigms. Within this category, we detail a wide variety of hybridization approaches.

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<sup>2</sup> See references in <http://www.statmt.org/survey/Topic/SystemCombination>.

## Hybridization of MT Architectures

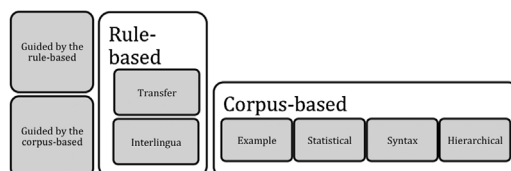


Fig. 1. Classification of hybrid MT architectures.

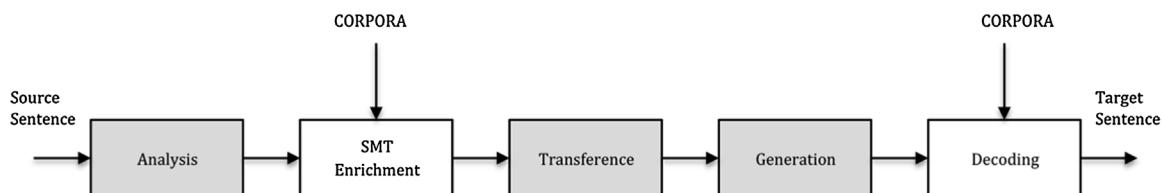


Fig. 2. Schema of hybridization guided by RBMT.

### 3. Hybridization of machine translation architectures

Several different methodologies have been used to hybridize MT within and across paradigms. As shown in Fig. 1, hybridization of RBMT and corpus-based MT can be classified into those guided by RBMT or guided by corpus-based MT. The former integrates data information into a rule-based architecture; the latter integrates linguistic rules into a corpus-based architecture.

#### 3.1. Hybridization guided by RBMT

There are several kinds of strategy within this category: introducing a corpus to build the RBMT system, introducing corpus-based tools to weight the RBMT output and carrying out a statistical post-editing of a RBMT output.

*Using a corpus to build the RBMT system.* The main reason for using data when building a RBMT system is to reduce its cost and the time and effort required. A quite straightforward approach is to enhance dictionaries with phrases (Habash et al., 2009) or examples (Sánchez-Martínez et al., 2009; Antonova and Misyurev, 2014) extracted from parallel corpora, and extract new entries from BabelNet and Wiktionary (Göhring, 2014). More complex approaches extract transfer rules (Sánchez-Martínez and Forcada, 2009), build lexical selection modules using parallel corpora with finite-state transducers (Tyers et al., 2012) or Maximum Entropy Markov Models (Rudnick and Gasser, 2013), and combine several of these techniques (Costa-jussà and Centelles, 2015).

*Corpus-based tools for weighting the RBMT output.* There is work that focuses on improving the RBMT output by integrating tools such as language models (Dove et al., 2012) or stochastic parsers (Federmann and Hunsicker, 2011). Papers like Labaka et al. (2014) show a hybrid translation system guided by the RBMT engine and, before transference, a set of partial candidate translations provided by SMT subsystems is used to enrich the tree-based representation. The final hybrid translation is created by choosing the most probable combination among the available fragments with a statistical decoder in a monotonic way (see Fig. 2). In addition, there are RBMT systems that introduce machine learning techniques such as classifiers in order to identify the set of *appropriate* translation candidates (Hunsicker et al., 2012). Recent experiments by Systran build a statistical inference module to replace the RBMT transfer module (Crego, 2014) and experiments by Lingenio show that RBMT systems can learn morphological classification, semantic and syntactic information from corpus data (Eberle, 2014).

*Statistical post-editing of RBMT outputs.* There are studies that carry out statistical post-editing for RBMT systems (Simard et al., 2007; Lagarda et al., 2009) and it is even a commercial reality<sup>3</sup> as pointed out in Béchara et al. (2012). Generally speaking, these approaches consider RBMT outputs as source sentences and post-edited results as target

<sup>3</sup> <http://www.systran.co.uk/translation-products/server/systran-enterprise-server>.

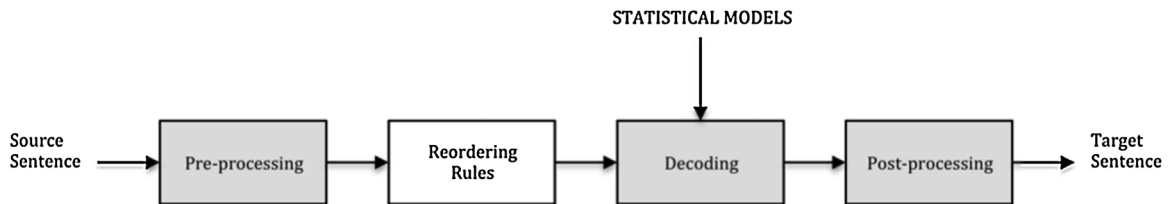


Fig. 3. Schema of hybridization guided by corpus-based MT.

sentences. In other cases, [Suzuki \(2011\)](#) confidence estimation measures are used instead of manually post-edited results. The statistical module tends to be implemented with Moses ([Koehn et al., 2007](#)). In this case, RBMT and SMT paradigms are concatenated but not integrated at the architecture level.

### 3.2. Hybridization guided by corpus-based MT

A hybrid system guided by corpus-based MT may incorporate rules or just combine various corpus-based MT approaches. There are basically two main ways of integrating rules into corpus-based MT approaches: using rules at pre/post-processing, and integrating dictionaries/rules into the core model.

*Rules at pre/post-processing.* Pre-processing rules have been used to reorder the source sentence into a form that better matches the target language ([Xia and McCord, 2004](#); [Collins et al., 2005](#); [Wang et al., 2007](#); [Patel et al., 2013](#)). The schema for this type of strategy is shown in [Fig. 3](#).

Post-processing rules for morphology generation have been introduced by means of a combination of machine learning and the introduction of dictionaries ([Formiga et al., 2012](#)).

Finally, a set of both pre-processing and post-processing rules have been compiled ad-hoc for the Spanish-Catalan translation pair in [Farrús et al. \(2011\)](#), in order to solve the normalization problems typically found in noisy corpora.

*Incorporating dictionaries/rules into the core model.* Rules may be integrated into the core model of corpus-based MT approaches. Early work such as [Carl et al. \(2000\)](#) integrates morphology and syntax knowledge from the RBMT system dynamically into an EBMT system. In other cases, RBMT systems have been integrated into the phrase-based SMT modules. For example, [Hua and Haifeng \(2004\)](#) use RBMT information to improve statistical word alignment. Then, [Eisele et al. \(2008\)](#) augment the standard phrase table with entries obtained after translating the data with several RBMT systems. The resulting phrase table thus combines statistically gathered phrase pairs with phrase pairs generated by linguistic rules. Similarly, [Sánchez-Cartagena et al. \(2011\)](#) enrich the phrase table with bilingual phrase pairs matching transfer rules and dictionary entries from a shallow-transfer RBMT system, and carrying out a comparison with an earlier paper ([Eisele et al., 2008](#)). Further work by these latter authors ([Chen and Eisele, 2010](#)) integrates a commercial RBMT system with a hierarchical SMT system by extracting rules from RBMT translations. The hybrid system inherits the lexicons from both sub-systems as well as local syntactic constructions defined in RBMT.

From a different perspective, [Ahsan et al. \(2010\)](#) focus on integrating local and long reorderings as well as the generation module from an RBMT system, into the core translation model of a standard statistical system. Furthermore [Enache et al. \(2012\)](#) introduce rules from a grammar formalism into the phrase table, and [Okuma et al. \(2008\)](#) introduce dictionaries into the phrase table to reduce the number of unknown words.

*Hybridization within corpus-based approaches.* When combining corpus-based approaches, [Groves and Way \(2005\)](#) mix sub-sentential alignments from phrase-based SMT and EBMT systems, proposing to build a hybrid ‘example-based’ SMT system incorporating marker chunks and SMT sub-sentential alignments. There is an extensive body of work on incorporating translation memories (TM) into phrase-based SMT systems. TM are simply large databases of translated words and sequences of words, generally created by human translators. One of the most recent studies ([Wang et al., 2013](#)) proposes integrated models to make maximum use of TM information during decoding. The aim is to keep all its possible corresponding target phrases for each TM source phrase. The integrated models then consider all corresponding TM target phrases and SMT preferences during decoding. Therefore, the proposed integrated models combine SMT and TM at a deep level. A traditional way that cannot be neglected is the use of templates ([Och and Ney, 2004](#)), which themselves can be considered to be stochastically-extracted transduction type rules. There are also approaches that combine n-gram and phrase SMT in series ([Costa-jussà and Fonollosa, 2010](#)). The former pre-reorders the source sentences and offers a reordering graph that the latter translates using monotonic decoding.

Table 1  
Hybrid MT architectures, added information and the corresponding most representative references.

Guided by	Information	References
RBMT	Corpus to build	Habash et al. (2009), Sánchez-Martínez et al. (2009), Antonova and Misyurev (2014), Göhring (2014) Sánchez-Martínez and Forcada (2009), Tyers et al. (2012), Rudnick and Gasser (2013), Costa-jussà and Centelles (2015)
	Corpus to weight outputs	Federmann and Hunsicker (2011), Dove et al. (2012), Hunsicker et al. (2012), Labaka et al. (2014), Crego (2014), Eberle (2014)
	Statistical post-editing	Simard et al. (2007), Lagarda et al. (2009) Suzuki (2011), Béchara et al. (2012)
Corpus-based MT	Rules at pre/post-processing	Xia and McCord (2004), Collins et al. (2005), Wang et al. (2007), Patel et al. (2013), Farrús et al. (2011), Formiga et al. (2012)
	Dictionaries/rules into the core model	Carl et al. (2000), Hua and Haifeng (2004), Okuma et al. (2008), Eisele et al. (2008), Sánchez-Cartagena et al. (2011) Chen and Eisele (2010), Ahsan et al. (2010), Enache et al. (2012)
	Only corpus	Och and Ney (2004), Groves and Way (2005), Wang et al. (2013) Carbonell et al. (2006), Carl et al. (2008), Costa-jussà and Fonollosa (2010), Tambouratzis et al. (2013)

Finally, there are approaches that are exempt from the requirement for parallel corpora or resources in general. There is an MT method that needs no parallel text and relies on a translation model built from a bilingual dictionary, and a decoder for long-range context (Carbonell et al., 2006). In the same direction, other systems use low resources (Carl et al., 2008) and a methodology designed to facilitate rapid creation of the MT system for unconstrained language pairs (Tambouratzis et al., 2013) (Table 1).

#### 4. Machine translation applications with hybrid components

Among the variety of MT applications, we can name popular ones such as speech translation, cross-lingual information retrieval and computer-aided translation. Hybridization within these applications has been used in different ways and we offer comments some of them without aiming to be exhaustive. See Fig. 2 for a short summary of references.

*Speech translation.* Frequently, speech translation is addressed as a concatenation of a speech recognizer, a machine translator and a speech synthesizer. Hybridization in this application can be placed in any of the three systems. In speech recognition, hybridization has been done by incorporating neural network approaches into state-of-the-art continuous speech recognition systems based on hidden Markov models (HMMs) (Bourlard and Morgan, 1993). There is also the combination of hidden Markov models (HMMs) and learning vector quantization (LVQ) (Katagiri and Lee, 1993), or the use of Support Vector Machines (SVMs) for classification by integrating this method into a HMM-based speech recognition system (Ganapathiraju, 2002). In text synthesis, the hybridization has been done by combining concatenative synthesis and statistical synthesis (Tiomkin et al., 2011).

*Cross-lingual information retrieval.* Normally, the application of cross-lingual information retrieval is done by concatenating MT and information retrieval. For example, Mittal et al. (2010) present a hybrid information system combining: (1) an ontology for the retrieval of user's context (2) a user profile that is temporarily updated according to user's browsing behavior and (3) collaborative filtering for considering recommendations of similar users. Elsewhere, Rose and Belew (1989) use a combination of symbolic and connectionist artificial intelligence techniques.

Table 2  
Hybrid MT applications.

MT applications	References
Speech translation	Bourlard and Morgan (1993), Katagiri and Lee (1993), Ganapathiraju (2002), Tiomkin et al. (2011)
Cross-lingual information retrieval	Mittal et al. (2010), Rose and Belew (1989)
Computer-aided translation	Wong et al. (2012), Yamabana et al. (1997), Federico et al. (2014)

*Computer-aided translation.* Finally, computer-aided translation is by definition a combination of the roles of both man and machine. Recent work, like (Wong et al., 2012), uses a machine-aided translation system, which is a hybrid system that applies not only TM technology but also MT methodologies, including the annotation schema of Translation Corresponding Tree (TCT) in the representation of bilingual examples, and the language formalism of Constraint-based Synchronous Grammar (CSG) in analyzing the syntactic structure between the languages; Yamabana et al. (1997) also propose a hybrid interactive MT method that combines rule and example-based MT approaches with an interactive man-machine interface. Advanced work in the field such as (Federico et al., 2014), includes approaches to incremental training or active learning which are representative of live human-machine hybridization where the MT system learns and improves based on human interaction.

## 5. Conclusions

This survey reported an overview of several relevant works on hybrid MT which combine different MT architectures to provide better translation quality. Combinations aim at extracting the best features of each paradigm and solving the problems of pure architectures. That is why hybrid MT has helped to advance the field and is a promising line of research.

This paper provides a structured classification that can cover the majority of research on hybrid MT. The classification is based on the fact that combinations of MT approaches are normally guided by a core system which can be either rule or corpus-based. Most of the research combines sources of information (rules and data), but there are also projects combining various corpus-based approaches. It is difficult to assess which is the most relevant or promising hybrid type of architecture, but it would seem reasonable to use the best-performing system as a guide, and the others for additional information.

The good results produced by hybridization have led to a corresponding spread of MT applications such as speech translation, cross-language information retrieval, computer-aided and post-edited MT systems. Work with hybrid strategies in both in MT and its applications brings significant improvement because they allow the simultaneous exploitation of a variety of systems.

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