July 23, 2013

Contents

Chapter 1

Introduction

> *When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.*

Evidently, automatic translation is not as easily solved as Weaver thought at the time. Over 60 years later, the state-of-the-art systems are still not able to produce translations of an arbitrary text with a quality compared to that of a translation of a human translator.

and many different methods have been investigated. This work focuses on one such method: compositional translation.

In many fields in which translations occur (computer science, logic, philosophy), computational translation is a very common method. The semantics of an expression in a certain logic, for instance, can be unambiguously determined by considering the terms and the methods used to combine them. Translating such an expression into another logical language can be effectively carried out by translating these terms and methods into the terms and methods particular for the second logic.

However, none of this teaches us if compositional translation is a reasonable strategy for translating natural language. Intuitively, it seems reasonable that 'who-did-what-to-whom-relations' are universal for languages, but exploiting this fact in translation has proven to be a non-trivial task. The present work does not aim to develop a model for compositional translation of language, but rather attempts to empirically analyse if it is realistic to aim for one.
Although this question is of theoretical nature, blabla explain that we have to deal with data such that it merely transforms to the question: can we find compositionality in the corpora we are training on, that an be of use in translation models. We will therefore also pay some attention to the use of the results, and make suggestions for future work.

Thesis Outline

As mentioned before, the primary goal of this thesis is to investigate whether predicate-argument relations are preserved during translation. To do so, a tree will be searched that respects both the alignment (completely) and as much of the predicate-argument relations present in the source sentence as possible. The resulting tree will be scored according to how many of the predicate argument relations were allowed by the alignment, thus yielding a compositionality measure for the sentence.
The following chapter will give some theoretical background: it will explain the notion of alignment-respecting trees (anders) and provide some information on the grammar formalism used to extract predicate-argument relations.
Chapter give more information on the implementation of the research, while the actual experiments and their results will be presented in chapter

Chapter 2

Transfer Models in Machine Translation

Machine translation (MT) is a very complex problem, to which many approaches have been tried. In this thesis, we focus on one such approach: the transfer method. We will start with two introductory sections, describing the early days on MT, that may be skipped by readers well familiar with MT. Hereafter, in section 2.3 we will discuss transfer-based models. We do not claim to give a complete overview of these; MT is an enormous field in which many models have been developed, most of which are hybrid in the sense that they borrow from different approaches to complete different parts of translation. For more complete overviews of MT and SMT, the reader is referred to Hutchins and Somers (1992) (MT), Somers (1999) (EBMT) and Koehn (2008) (SMT).

2.1 Early Machine Translation

Machine translation rose as a field of research almost immediately after the emergence of the first computers, and was one of the very first problems to be tackled by computers. The very first approaches to solve the problem, also called the first generation approaches, were more or less direct: sentences were treated as structureless sequences of words that can be directly mapped to words in another language. Using this approach, relations between words or other structural aspects of the sentence are thus not considered. Clearly, such a strategy is only reasonable if the source and target language are structured almost identically: a translation whose structure deviates from the structure of the original sentence will never be found. Unfortunately for MT researchers, natural languages are not ordered in this fashion, and the direct approach of the first generation models was not very successful. First generation models regularly lead to translations that were incomprehensible, not fluent or not even meaning preserving.
The failure of the first generation models lead to a second generations of models,

using indirect methods that laid the groundwork for the models considered in this paper. The main idea of the second generation systems was to analyse the source sentence into an intermediate representation somehow conveys the semantic structure (or 'meaning') of the sentence, and map this representation to an intermediate representation in the target language. From this intermediate representation, the translation of the sentence in the target language could be derived. The process of mapping representations in one language to representations in another is called transfer.
An extreme case of the transfer method is the one in which the intermediate representation is a universal one. Such a representation, called interlingua, can be seen as a description of the meaning of the sentence independent of any natural language. The transfer part is reduced to the identity mapping, and translation consists of translating the sentence into an independent meaning representation and deriving the target sentence from this representation. As it addresses translation on a fundamental level this is attractive from a theoretical point of view, but it is very hard, especially when the meaning space is unrestricted. Some researchers have succeeded in writing rather successful translation models for very small domains (give examples?), but nowadays, finding a formal semantics that can capture all of human language is an independent research field, in which a satisfiable interlingua has not yet been found.

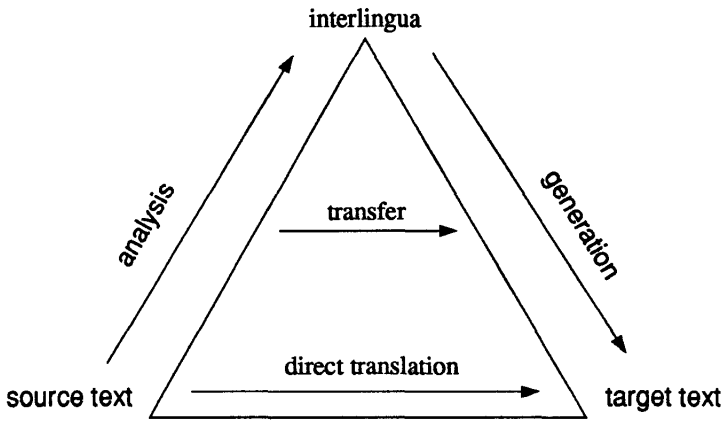

Figure 2.1: Vauquois pyramid?

The three translation methods described can be placed in a pyramid (2.1), to show how they are related. This pyramid also shows that the transfer method can be employed in different ways, varying the distance from source and target text to intermediate representation (analysis and generation, respectively), and with this the distance between the intermediate representations. In this sense, interlingua and direct translation can be seen as two inflexible extremes this method.

2.2 Early Statistical Models

Driven by the thought that language is too rich to formalize, a new line of research came of the ground, that was not primarily based on linguistic knowledge, but on large pairs of text that were translations of each other (parallel corpora). In the beginning, the corpus based systems seemed to rival the existing linguistically oriented paradigm, but soon people concluded that the two approaches were not actually conflicting, and nowadays most models combine the two of them.
Corpus based models can be roughly divided into two main categories.[1] Models of the first category are directly based on analogy. When translating a sentence, they try to find examples in the corpus similar to (fragments of) the sentence and generate a translation by recombining them. This part of machine translation is often called Exemplar Based Machine Translation. The early MT researchers had the misfortune that computational standards were not as they are today and their models often only treat small sublanguages, are computationally not executable and certainly not scalable. Although of theoretical interest, the early EMBT models will therefore not be discussed. Many of the idea's investigated came back in later papers about MT (e.g. consider Furuse and Iida's (1992) hierarchical phrases), although it is unclear if they were inspired by earlier papers or just reinvented.
The second category of corpus-based models is more interesting to the current work. In models of this category, appositely called statistical machine translation models, parallel corpora are not used to match and recombine, but to statistically decide on the parameters of another model. Even though the first statistical models seemingly took a step back, moving towards the direct translation approach again, and considered no linguistic information whatsoever, they were (at least result wise) an enormous improvement over any model existing at the time. As these systems were primarily word-based, they do not fall into the category of models discussed in this thesis. However, the models we will discuss are founded on the notions and concepts introduced with these first word-based models, so we will devote a section to them (and their phrase-based extension) nevertheless, before getting back to transfer-models.

2.2.1 Statistical Word-based Models

The first working statistical MT model, inspired by Weavers idea to use information theory to reach automatic translation (Weaver, 1955), was presented by Brown et al. (1990). This paper was based on earlier work of the same research group (Brown et al., 1988), and was further worked out in a later paper (Brown et al., 1993). Their models, now known as 'IBM model 1-5' follow the noisy channel approach, modelling the probability $P(t|s)$ that t is the translation of s.[2] This probability is then expressed using Bayes' theorem resulting in the

[1] Although this division has some theoretical ground, it is mainly suggested to be able to distinguish work that is interesting for this paper and work that is not.

[2] In the literature, this probability is often expressed as $P(e|f)$, as the first IBM models modelled translation from French to English. However, this can be quite confusing for the

following expression (called “The Fundamental Equation of Machine Translation" by the authors) for the desired translation $\hat{t}$:

$$\hat{t} = \arg\max_t P(t)P(s|t)$$

The translation task is now split in two: modelling the translation probability $P(s|t)$, and modelling the language probability $P(t)$. The model for $P(t)$, that is standard an n-gram model, accounts for fluency and grammaticality of the target output. The generative model is standard in information theory, the crux of the model resides in how $P(s|t)$ is modelled. In the IBM models, this distribution is modelled by marginalizing over all possible ways in which the words in t could have been generated by the words in s, thus $P(s|t) = \sum_a P(s, a|t)$, in which a describes the mapping from target to source words. The 5 IBM models differ in the complexity of the approximation of the conditional probability $P(s, a|t)$, ranging from a very simple distribution in which a is not considered at all (in which case the probability is independent of word-order) to rather complex ones in which a is dependent on several parameters (details can be found in Brown et al. (1993)).
All IBM models require a lexical translation probability (i.e., a dictionary like function that specifies the probability of word w_s translating into w_t. These probabilities are not directly observable from the parallel corpus (as the corpus is sentence aligned but not word aligned) and are learned from the data applying the expectation maximization algorithm, that is proved to converge to a global optimum. Nowadays the IBM models are outperformed by newer sophisticated models and not in use anymore, but their techniques for generating word-alignments are still often used to analyse translation data or to generate training data for newer models.

2.2.2 Statistical Phrase-based Models

The statistical IBM models lead to a huge improvement in translation quality, but they still had the same drawbacks as the first generation of direct translation models: no structure or local context was considered and a large amount of natural language phenomena could therefore not be accounted for. A major leap forward was taken with the introduction of (non linguistic) phrases as basic units in translation models (Wang (1998); Och et al. (1999)??). A phrase translation pair is a pair of contiguous source and target sequences such that the words in the source phrase are aligned only with words in the target phrase, and vice versa. (Och and Ney, 2004). Phrases are thus not restricted to linguistic phrases, but can be any arbitrary contiguous sequence of words. Keeping the architecture (more or less) the same, using phrases instead of words as translation units allows the model to use local context during translation. Phrases based translation models can therefore capture short contiguous idiomatic translations, as well as small insertions and deletions and local reordering. E.g. both ‘a casa’

reader, and in this paper we will stick to the more general t for target and s for source.

and ‘o casa’ are reasonable word-for-word translations of the English phrase ‘the house’. However, ‘o casa’ is not a grammatical string in Portugese. The latter observation could be easily captured by a phrase-based model, as ‘the house’ could be translated as one unit, but would be much harder to model in a word-based model. Furthermore, a word-based model would never be able to get the correct idiomatic translation of a phrase like ’kick the bucket’, while a phrase-based model would have little trouble finding this translation (provided this specific idiomatic phrase was present in the training corpus). However, such models still suffer from the fact that no structure beyond the phrase level is taken into account.[3] Attempts to incorporate syntactic structure by linguistically motivating the selection of phrases (Koehn et al., 2003) turned out unfruitful, and the focus of the MT-world shifted back to more structure-based models.

2.3 Statistical Transfer Models

The shift of the field to more transfer-based models did not happen overnight. Some researchers were exploring statistical rule-based models even before the first phrase-based model was presented. Over the last 15 years, *very* many models exploring structure beyond the phrase-level have been presented, many of which were hybrid models combining several different strategies. In this section, the focus lies on the different strategies that have be employed to find a mapping between source and target language structures. This means that this section is by no means a complete overview of the statistical syntax-based translation models. We will not discuss approaches that use the recursive properties of languages without explicitly searching for a mapping, excluding for instance approaches that use syntactic structure as features in a log-linear model (e.g. Cherry (2013); Liu and Gildea (2010)), for reordering preliminary to translation (e.g. Khalilov and Sima’an (2012)) or to rerank output of a standard phrase-based system (e.g. Och et al. (2004)). Also, we will not discuss the methods used to learn a probability model over the selected rules, nor will we discuss decoding or give details on the performance of the models as it is often hard to tear apart whether performance is due to improved mappings or other factors (as better decoding strategies, different datasets or a better probability model). Note that the models are not presented in a chronological order, but are merely grouped according to similarity.

2.3.1 Synchronous Context Free Grammars

The lion’s share of the statistical transfer models searches for a bijective relation between source and target structure, hereby assuming that former and latter are isomorphic. The grammars and relation between them can be formalized as a synchronous context free grammar, simultaneously generating source and target

[3] Moreover, phrase based translation knows many practical problems, that will not be further discussed here. A rather detailed discussion of the (theoretical and practical) problems with phrase-based translation can be found in Quirk and Menezes (2006a)

structure. Even approaches that are not explicitly concerned with SCFG's can often be interpreted as such. An SCFG is defined as a set of rules of the form:

$$X \rightarrow \langle \gamma, \alpha, \sim \rangle$$

In which γ and α are sequences of terminals and non terminals in the source and target language, respectively, and $\sim$ is a one-to-one correspondence between γ and α, indicating that they are translation equivalent. SCFG's implicitly model reordering phenomena and non-contiguous phrases.

Strictly Linguistic SCFG's

In a purely linguistic SCFG, γ and α are restricted to rules allowed by linguistic monolingual grammars. The SCFG is then found by parsing both source and target sentences with a linguistic parser and aligning the trees on the node level. Although a number of early attempts can be found (see Wu, 1997, p. 20), there are no recent approaches using such a 'parse-match-parse'-method on the context-free level. As monolingual grammars are not designed for translation purposes it is often impossible to statistically align every source tree node to a target tree node, because the trees are not isomorphic.[4] Current translation models whose rules are based strictly on monolingual grammars are therefore rarely context-free. Furthermore, the 'parse-match-parse' method requires appropriate and robust monolingual grammars on both source and target side, as well as high quality parsers, which clearly restricts the number of languages pairs that can be treated in such a way.

Strictly Formal SCFG's

Wu (1997) presents a model that attacks the weaknesses of the purely linguistic approach. His framework, the inversion transduction grammar (ITG) is at the heart of many later approaches. Also the ITG framework can be formulated as an SCFG, and thus does not differ from aforementioned linguistic approaches in this aspect. However, ITG-rules are not restricted to linguistic rules, but are motivated by the translation data. The nodes in the tree are thus not necessarily linguistic constituents, but can cover any part of the sentence, as long as a translation equivalent span can be found in the other sentence. In this context, translation equivalence is defined in terms of alignments: a source and target phrase α and β are translation equivalent if words in α are linked only to words in β and vice versa. For isomorphic trees, it is added that α and β are contiguous sequences in source and target sentence, respectively.
Learning formal grammar rules is associated with computational issues. Without a restriction on labels or the rank of the rules, the number of rules that can be extracted from a sentence of length n grows exponentially with n and hence it is impossible to include them all in a grammar. Several solutions have been

[4] Often, it would be possible to design more compatible grammars for the languages, if the goal of translation was kept in mind. (anders) A more detailed discussion of this issue can be found in Rosetta (1994).

proposed to this problem. Wu himself restricts his grammar to (left-branching) binary trees with a single non-terminal, asserting that he was unable to find any real-life examples of translations that could not be explained by such trees. Chiang (2005) constructs a grammar with rules containing both non-terminals (once again only a single non-terminal label is used) and terminals. The number of such translation rules is still very large ($\mathcal{O}(n^6)$ for a 1-1 monotone sentence pair (Quirk et al., 2005)), Chiang prunes his rules by, i.a., putting restrictions on the length of the terminal sequences on both sides, as well as on the rank of the rules. The framework introduced by Chiang, combining the strengths of rule-based and phrase-based translation models, is often called hierarchical phrase-based translation.
Another phrase-based hierarchical model was presented in Mylonakis and Sima'an (2010). The set-up is similar to Chiang's (2007), but two extra non-terminals are added to decode whether a phrase-pair tends to take part in order switching, and the rules are restricted to binary. They show that it is possible to train a complete all-phrase binary grammar with cross validated EM. Blunsom et al. (2008) use a corpus to induce non-terminal categories for phrasal translations, using a Bayesian model.

Linguistically motivated formal SCFG's

A way of limiting the number of rules in a more guided way is to use linguistic knowledge to reduce the space of possible node spans. Although such a strategy is not possible for every language pair, as it reinstates the second problem of purely linguistic transfer models, using available syntactic or semantic knowledge can result in robust models that yet do not ignore our knowledge of language and, moreover, simplify the parsing process. Both Zollmann and Venugopal (2006) and Almaghout et al. (2010) gained performance by augmenting grammars with syntactically motivated non-terminal labels, based on standard constituency grammars and ccg, respectively. Li et al. (2013) integrated more semantically oriented notations in a standard hierarchical phrase-based system.

2.3.2 Beyond Context Free

Although this is formally desirable, there is no a priori reason to assume that it is possible to find isomorphic tree pairs for sentences that are each others translation. More powerful transformation methods might be more suitable for the expressive syntactic transformations going on in translation of natural language. As the necessity of deviating from conventional syntax is smaller, models of this class tend to stay closer to traditional linguistic structures.

Synchronous Tree Substitution Grammars

The class of Synchronous Tree Substitution Grammars (STSG's) is a strict superset of the class of SCFG's, and STSG's are therefore a natural extension to them. Models working with STSG's are, i.a., Poutsma (2000) and Galley et al. (2004,

2006). The core method of the former is to align chunks of parse trees of source and target sentences, and transform them into rules. Poutsma (2000) requires the existence of a parallel corpus aligned on the subtree level. Such datasets were not available and the paper is merely a description of the STSG framework. The model presented by Galley et al. has a somewhat different set-up, learning rules to transform an source-language string into a target language tree. Galley et al. (2006) does provide an implementation, yielding promising results.
An approach that does not explicitly use STSG's, but whose grammar rules do exceed the power of CFG rules, is presented by Melamed et al. (2004). In their generalized multitext grammar (GMTG) they let go of the requirement that constituents need to be contiguous, which allows them to synchronise languages generated by mildly context-sensitive languages. (anders) Also Melamed et al. present a framework with suggestions for further work, rather than an implementation.

Semantic Mappings

The last category of models we will discuss, attempts to find mappings between more semantically oriented structures, that specify the predicate-argument structure of the sentence, that is often assumed to be somewhat universal. Such an approach is taken in Menezes and Richardson (2003), in which transfer rules are extracted by aligning pairs of Logical Form structures. Another predicate-argument structure that is often used is the dependency parse (ref??), rules are inferred by either projecting or learning target-side paths. As such rules sometimes create or merge dependents according to the alignment, the dependency structures of source and target side need not be isomorphic, and such models can formally also be seen as STSG's (as made explicit in Eisner (2003)). Finding a mapping between two dependency trees is not only attractive because dependency trees represent the semantic structure of a sentence more closely than a constituency tree, but also because it is computationally more feasible, as dependency trees contain fewer nodes than constituency trees of the same sentence. Presented models differ in the linguistic plausibility of the target side dependency parse. E.g., Eisner (2003) learns mappings between two dependency trees (his article lacks a working implementation, although it does give a description of algorithms suitable for parsing with his model). Lin (2004), extracts transfer rules that correspond to linear paths in the source side dependency tree, but not necessarily to linguistic dependency parses on the target side. The models presented in Quirk et al. (2005); Quirk and Menezes (2006b,a) also have clear dependency part, but employ several other strategies as well. They project source dependency trees to target dependency trees, following a set of rules, and extract from the resulting corpus a set of *treelets* - arbitrary connected sub graphs - that are used in translation.

Chapter 3

The theoretical backbone of transfer models

As seen in the previous chapter, syntax-based models attempt to find structural representations of sentences in different languages and a function that maps the representations of sentences in one language to the representations of sentences in another if and only if the sentences are each others translation. The types of grammars (the objects generating the representations) and the mappings between them differ from model to model. What these models have all in common, is that they assume that such grammars and mappings exist. In this chapter, we will explain and analyse what the implications of these assumptions are for natural language. (anders) We claim that these assumptions are in fact equivalent to the well-known principle of compositionality of translation:

> Two expressions are each others translation if they are built up from parts which are each other's translation, by means of translation-equivalent rules (ref??)

Evidently, if translation between any two languages obeys this principle, representational systems and mappings between them can be found. Conversely if two (tree) representation and a function between them can be found, this function can be seen as a translation-equivalent rule and its input and output as parts and their translation.

The principle of compositionality of translation holds some thoughts on how translation ought to be. We will discuss these thoughts in the following sections.

3.1 Compositionality of Language

On of the assumptions constituting the principle of compositionality of translation is that languages can be described by means of a compositional grammar, i.e. they are compositional themselves. Compositionality is a property possessed by

most artificial languages. The meaning of an expression in a logical language, for instance, can be unambiguously determined by considering the atoms and the rules used to combine them. For programming languages, a similar statement can be made. The following principle, analogous to the principle of compositionality of translation and known as 'the compositionality principle' describes this property:

> Meaning of an expression is a function of the meaning of its parts and syntactic rule by which they are combined Partee (1984)

To what extend natural languages can said to be compositional is an issue that has yet to be sorted out. Although the compositionality of some part of natural language is undeniable - we can understand sentences we have never heard before because we know the words in it and we are familiar with the methods that can be used to combine them - many have argued against compositionality of natural language as a whole. An often heard counter argument is the existence of idiomatic expressions, whose meaning can clearly not be derived from the meaning of its parts, and scope and reference ambiguities.[1] As for the latter, it is hard to even make a statement about this with the principle as given above, that is highly underspecified. The power of a compositional grammar depends a great deal on the notion of parts meanings and rules in this grammar. That is to say, in theory it is possible to include all idiomatic expressions along the words as basic units in the grammar (in some cases this might result in a grammar that intuitively does not at all seem compositional any more).

There are a couple reasons why an elaborate discussion of the compositionality debate is outside the scope of this paper. Firstly, the main contribution of this paper is an empirical analysis of the level of compositionality that can be found in translation data. Although this question has a theoretical background, as we are are working with real life data, the answer will have a practical nature, and will hopefully show if languages contain *enough* compositionality to be useful in translation. Secondly, arguments against compositionality are often focussed on ambiguous sentences that cannot be assigned distinct syntactic structures. However, disambiguation is a separate issue in MT, that this paper is not concerned with. Moreover, note that these kinds of ambiguity causing non-compositional meaning derivations do not necessarily have to be a problem for translation. Consider for instance the sentence 'Two men carry two chairs'. Although this type of ambiguity is troublesome for a compositional analysis (Pelletier, 1994), it does not impair the possibility of compositionally translating to Dutch, as the Dutch sentence 'Twee mannen dragen twee stoelen' is ambiguous in the exact same way. (dit is echt een draak van een zin)

An detailed discussion of compositionality by one of the advocates of compositionality can be found in Janssen (1996).

In this paper, Janssen also shows that although not every grammar is suitable for compositional meaning assignment, the class of languages that can be analysed is not restricted, nor are the meanings that can be assigned: any recursively

[1] I undoubtedly do the arguments against compositionality short (??), but a detailed discussion of compositionality is outside the scope of this paper... (anders)

enumerable language can be generated by a compositional grammar, and any semantics can be dealt with in a compositional way. *Finding* algebra's that describe the meaning and syntax of a language is of course not a trivial task.

3.2 Translation is Literal

Apart from assumptions about the languages involved, the principle of compositionality of translation also makes assumptions about the translation process itself. First of all, it assumes that translation should not only preserve meaning, but also form (as much as possible). In other words, it assumes that translation is literal. Generally, this is helpful when deciding about the adequacy of a translation. An example that illustrates this is the following: *all ravens are black* is an adequate translation of the Dutch *alle raven zijn zwart*, but the logical equivalent sentence *if something is not black it is not a raven* is not (Landsbergen et al., 1989). However, even without regarding idiomatic translations, that will be considered later, a translator can have many reasons to prefer a more free translation, even if a literal alternative is present. Although this is a real issue in practice, machine translation is by far not developed enough to be concerned with style issues and throughout this paper will be assumed that translation is as literal as possible.

3.3 Translation is Compositional

After having discussed two important assumption that underpin the principle of compositionality of translation, we get to the main point of the principle (ander): translation is compositional, i.e. there exist a systematic mapping between the compositional grammars of two languages. GIve some examples of seemingly non-compositional phenomena that can still be treated compositionally (Landsbergen et al. (1989), Rosetta (1994))

Chapter 4

An Empirical Study

In articles about syntax-based translation models the assumptions discussed in the previous chapter are are rarely mentioned, let alone questioned. Moreover, the evaluation of the models presented is based on the performance of an implemented version of them that only approximates the theoretical solution due to simplifications made during encoding. Furthermore, the hybrid nature of models makes the evaluation of the transfer part even fuzzier, as it is not clear which parts of the model are responsible for the results. The current work deviates from this research, in presenting an exploration of the underlying assumptions. Such an analysis is of theoretical importance, but can also serve as an estimate of how far syntax-based translation models can actually bring us and possibly lay the basis for a new type of MT model.
The current chapter describes the contribution of this. The outline of the chapter is as follows: we will first discuss a number of empirical studies on the recursive properties of translation data. Some of them are pure analyses, while others are mainly focussed on improving performance of a specific model or method, but report some empirical results during the process. Thereafter, we will present the founding for the contribution of this work, explaining the necessary concepts, and describing the experiment on a theoretical level. More details can be found in the Results chapter, implementation details can be found at the end of this paper in appendic A.

4.1 Related Work

Most empirical studies focus on the explanatory power of transforming linguistic parse trees. Even though they are ran on different datasets (and different language pairs) and use different criteria, they all find that permuting children in a linguistic constituency trees is not powerful enough to account for the reordering phenomena present in translation data, manual or automatic.

An often cited study is the one carried out in Fox (2002). Fox investigates the degree of phrasal cohesion across English and French. She counts the number

of times the alignment spans of constituents overlap or 'cross' in the corpus created by Och and Ney (2000), containing 500 manually aligned sentences from the Canadian Hansard corpus. The alignments are of type S (on which all annotators agreed) and P (in which annotators disagreed or were uncertain). She distinguishes 3 different conditions (only P, only S and S backed up with P), we will only report on her results including all alignment links. She concludes that crossings - even after filtering out phrasal translations that necessarily result in crossings - are too prevalent to ignore (on average 2.854 per sentence). Furthermore, she observes that dependency parses have better cohesive properties than constituency parses (2.714 per sentence).[1]

Her results are confirmed by others. Galley et al. (2004) concentrated on finding transformation rules based on larger fragments of trees. He plotted the coverage of the grammar against the maximum depth of the rules in the grammar, and found that only 19.4% of the parse trees in the corpus could be covered by one-depth transformation rules. At the node level, a comparison more similar to Fox's (2002) study, he finds a coverage of 85% for the S alignments. Furthermore, he finds that to cover the entire corpus the maximum number of rule expansions should be 17 for the S-alignments (and 23 for the Giza++ alignments). For the automatically aligned FBIS corpus (English-Chinese), the coverage of low-expansion rules was even lower: 16.5% for rules with a single expansion (child reordering scope) and 100% when the number of allowed expansions is no less than 43. Khalilov and Sima'an (2012) confirm the inadequacy of child-reordering in a work that is focussed on source reordering preliminary to translation. Using LRscore (Birch and Osborne, 2010) as a measure of success, they conclude that permuting the children of nodes in a constituency tree is insufficient to reach a perfect permutation of source-words in English-Dutch and English-Spanish translation data, even when deleting up to 5 layers of nodes in the parse tree is allowed.[2]

Hwa et al. (2002) investigate how well predicate argument structures correspond across English and Chinese, addressing the validity of the Direct Correspondence Assumption. Hwa et al. evaluate the quality of Chinese dependency parses that were projected directly from English to Chinese, according to a manual word alignment. The resulting parses had a very low F-score (38.1), which is not surprising, as phrasal translations (multiple aligned words on source or target side) and unaligned target words always result in errors. Hwa et al. (2002) make a similar observation, but did not aim for a scalable solution comparable to that of Fox. Rather, they developed a small set of linguistically motivated rules, that boosted the F-score significantly to 68.3, but is still rather low to be useful. Another work along this lines was presented by Fung et al. (2006) who learned cross-lingual (English-Chinese) semantic verb frames with argument mappings with 89.3% accuracy. It is unclear how their results compare to Hwa et al.'s

[1] With a manual analysis of the crossings in the constituency parses she shows that many of them are not due to the lack of phrasal cohesion, but are often caused by errors in syntactic analysis or rewording and reordering in the translation. Her analysis, however, included only the crossings of the S alignments, that constituted only a small part of the total set of crossings.

[2] Their score for English-Spanish, however, are surprisingly high: around 94

(2002).
Wellington et al. (2006) shows, that if the alignment trees are not restricted to parse trees, the results are much better, which brings us to a range of papers investigating the coverage of ITG on both manual and automatic alignments. A number of papers focussing on the binarizing SCFGs (Zhang et al., 2006; Huang et al., 2009) and the coverage of ITGs in normal form (Søgaard and Kuhn, 2009; Søgaard and Wu, 2009; Søgaard, 2010) all conclude that the range of reordering phenomena occurring in real translation data are by far not as complicated as the worst case sketched in Satta and Peserico (2005). Wellington et al. (2006) seem to be the only one who compare their results with linguistically restricted parse trees. On several dataset (covering translation from Chinese, Romanian, Hindi, Spanish and French to English), he found that maximally 5% of the alignments could not be explained by a completely binary tree, while the failure rate for binary trees that were constrained by monolingual parse trees on the English side climbed to 15% for French/English to 61% for Chinese/English. Their failure rate for non constrained binary trees is much lower than the one found by Sima'an and Maillette de Buy Wenniger, who reported a coverage of 71.46% for the manual alignments of the Hansard corpus for trees with a maximal branching factor of 2. The coverage of binary trees for automatic alignments was even lower: 52.84%. This difference between the results of Wellington et al. (2006) and Sima'an and Maillette de Buy Wenniger is most likely due to a different treatment of alignment links: the latter authors used all alignment links in the dataset, while the former treated many-to-one alignment links disjunctively, focussing on lower bounds. Sima'an and Maillette de Buy Wenniger also report the coverage of non binarisable (permutation) trees, which is surprisingly enough not much higher: 72.14% and 56.56% for manual and automatic alignments, respectively.

4.2 Original Work

The studies described in the previous section teach us that translation knows phenomena much richer than those covered by SCFG's and that using conventional syntax to improve systems is not as simple as one might hope. The study presented here, goes one step further, investigating the existence of compositional structures describing translations on a more general level. Following Wu (1997) and Wellington et al. (2006), we will study the recursive properties of translation data on the basis of alignments, disregarding conventional syntax at first. We will consider a set of structures that uniquely describe alignments, as defined in Sima'an and Maillette de Buy Wenniger, and aim for finding a systematicity in them that is able to explain the corpus. If such a systematicity exist, it is likely to generalise to new data, which is promising for transfer-based models. We will start by giving a formal definition of the set of structures, that can be considered summarising (parts of) Sima'an and Maillette de Buy Wenniger (although the notation in some of the definitions is slightly adapted to the convenience of this paper). We will then describe how we will use this set in our search for a

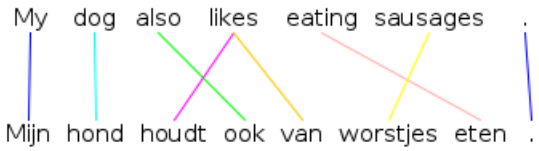

Figure 4.1: A one-to-many alignment of the English sentence 'My dog also likes eating sausages.' and its translation 'Mijn hond houdt ook van worstjes eten'.Maillette de Buy Wenniger et al. (2010)

consistent grammar for the corpus.

4.2.1 Hierarchical Alignment Trees

As the name suggests, an hierarchical alignment tree (HAT) is a tree defined over an alignment. Although we have no doubt that any reader of this thesis is familiar with the concept of alignment, for the sake of the completeness we will briefly exemplify.

Word Alignments

A word-alignment of a sentence pair is a mapping from source to target-words, that can be described by a set of arrows. An arrow from source word w_s to target word w_t implies that w_t was involved in the translation of w_s. An example of two aligned sentences can be found in 4.1). The precise definition of word-alignment varies from paper to paper, throughout this thesis we will use the following definition:

Definition 1 (Alignment)**.** *Given a source sentence $s = s_0 \dots s_n$ and its translation $t = t_0 \dots t_m$, an alignment $a \subseteq \{0, 1, \dots, n\} \times \{0, 1, \dots, m\}$ such that $(x, y) \in a$ iff s_x is translated into t_y.*

Note that the absence of a y such that $(x, y) \in a$ means that x is unaligned, and vice versa. In some definitions unaligned words are explicitly included in the alignment by adding an extra $NULL$ token to both source and target sets and including $(x, NULL)$ (or $(NULL, y)$) in a whenever word x (or y) is unaligned.

Alignments can be of several types, which will be of importance for the complexity of our algorithms. A summary can be found in table 4.1.

For the following definitions, we will introduce a change in notation. In our new notation, alignments are represented as extended permutations, in which numbers of the original sequence are allowed to appear more than once, or not at all. We will call such a representation a set-permutation. A set-permutation is defined as follows:

Definition 2 (Set-permutation)**.** *Given a source sentence $s = s_0 \dots s_n$, its translation $t = t_0 \dots t_m$, and an alignment a, let $a(i) = \{j \mid (i, j) \in a\}$ be the set*

one-to-one	$\forall x \forall y \big((x,y) \in y \rightarrow \forall z \big((z,y) \in a \rightarrow z = x \wedge (x,z) \in a \rightarrow z = y \big) \big)$
one-to many	$\forall x \forall y \big((x,y) \in y \rightarrow \forall z \big((z,y) \in a \rightarrow z = x \big) \big)$
many-to-one	$\forall x \forall y \big((x,y) \in y \rightarrow \forall z \big((x,z) \in a \rightarrow z = y \big) \big)$
many-to-many	-
monotone	$\forall w \forall x \forall y \forall z \big(((x,y) \in a \wedge (w,z) \in a \wedge x < w) \rightarrow y < z \big)$

Table 4.1: Alignment types, restrictions

with target positions that is linked to source position i. The set-permutation π uniquely describing a is defined as the ordered sequence of sets $\langle a(0), \ldots, a(n) \rangle$

The set-permutation $\pi = \langle \pi_0, ..., \pi_n \rangle$ describing the alignment showed in Figure 4.1 would thus be $\langle \{0\}, \{1\}, \{3\}, \{2,4\}, \{6\}, \{5\}, \{7\} \rangle$. In the following definitions it is assumed that there are no unaligned target-words (thus for a sentence with n words, $\bigcup_{i=0}^{n} \pi_i$ constitutes a contiguous sequence of numbers). The definitions can easily be extended to the case where there are unaligned target words, by only numbering the target positions that are aligned (effectively shifting the position numbers to the left whenever an unaligned word is found).

Translation Units

To define a tree over an alignment, we need to have a notion of allowed sub sequences. For this, we use a definition analogous to the definitions of phrase pair used in the first phrase based models (Och and Ney, 2004). For this we will use the notion of span:

Definition 3 (Span)**.** *Given a sentence $s = s_1 \ldots s_n$ with set-permutation π, a span $[i,j]$ denotes the subset $\pi_i \ldots pi_j \subseteq \pi$ corresponding to words $s_i \ldots s_j$*

A phrase pair is a pair of source and target spans [i,j] and [x,y], respectively, such that at least one word in [i,j] is aligned to at least one word in [x,y], and no words in [i,j] are aligned to words outside [x,y] and vice versa. The phrases consistent with the alignment are thus phrases whose translation is also a phrase. Translated in terms of a set-permutations π, we get the following definition for a translation unit:

Definition 4 (Translation unit)**.** *A span $[i,j]$ representing contiguous sequence $s_i \ldots s_j$ of a source sentence whose alignment is represented by a set-permutation $\pi = \langle \pi_0, \ldots, \pi_n \rangle$ is a possible translation unit iff the union $(\pi_i \cup \ldots \cup \pi_j)$ constitutes a contiguous range of integers, and for every integer $x \in (\pi_i \cup \ldots \cup \pi_j)$ holds that $x \notin (\pi_0 \cup \ldots \cup \pi_{j-1} \cup \pi_{i+1} \cup \ldots \cup \pi_n)$.*

The set of translation units consistent with the alignment in Figure 4.1 is thus: [0,0], [1,1], [2,3], [4,4], [5,5], [0,1], [2,3], [4,5], [1,3], [0,4], [2,5], [0,5]. In which

[x,y] includes all words from position x to position y. Note that the word 'like' is not a translation unit on its own, as it translates into two non-adjacent words in the Dutch target sentence. To cover such cases, we introduce 'discontinuous translation units', that refer to any pair of source and target sequences that translate into each other (and only into each other), but are not contiguous. A subsequence of a 'discontinuous translation unit' is an allowed part of the unit iff both its left and its right neighbour are not part of the unit.
The number of translation units in an alignment depends on the type of the alignment and is largest in case of a monotone alignment, that does not restrict the set of possible translation units at all. A completely monotone alignment of a sentence of n words has $\frac{n \times n+1}{2}$ translation units. Note that unaligned words can cause exponential growth in the number of translation units.

Alignment Trees

Given the set of translation units, we can define the set of structures according to which the sentence could have been compositionally translated. To define this set of structures, we firstly introduce the notion of a segmentation of a set-permutation.

Definition 5 (Segmentation of a set-permutation)**.** *Let $\pi = \langle \pi_0, \ldots, \pi_n \rangle$ be a set-permutation. A segmentation of π is an ordered set of indices $B = \{j_0 = 0, j_1, \ldots, j_{m-1}, j_m = n+1\}$ that segments π into m adjacent, non-overlapping and contiguous segments such that for all $0 \leq i < m$ holds that the subsequence $\pi_{j_i} \ldots \pi_{j_{i+1}-1}$ is either a translation unit or an allowed part of a discontinuous translation unit.*

For instance, a possible segmentation of our running example (recall: $\pi = \langle \{0\}, \{1\}, \{3\}, \{2,4\}, \{6\}, \{5\}, \{7\} \rangle$) would be $\{0,1,2,4,7\}$ as it divides the sequence in allowed spans $[0,0]$, $[1,1]$, $[2,3]$ and $[4,6]$. We can now define the set of alignment trees:

Definition 6 (Alignment tree)**.** *Given a source sentence $s = s_0 \ldots s_n$ and the set of its translation units $U = \{u_1, \ldots, u_m\}$. An alignment tree is any tree T satisfying the following four conditions:*

1. *$[0,n]$ is the root of the tree*
2. *For the set $N = \{n \mid n$ is a node in $T\}$ holds: $N \supseteq \{[i,i] \mid 0 \leq i \leq n\}$*
3. *For every node $n \in N$ holds $U \cup \{[i,i] \mid 0 \leq i \leq n\}$ or n is a word in the sentence*
4. *For every node $[i,j] \in N$ with children $[x_1, y_1] \ldots [x_n, y_n]$ holds: $x_k = y_{k-1} + 1$ and $\{x_1, \ldots x_n, y_n + 1\}$ is a segmentation of $[i,j]$*

An alignment may have many different possible alignment trees. The number of alignment trees can be exponential in the length of the sentence, if no restriction is placed on the branching factor of the nodes. Every alignment can be assigned at least one structure, that is completely flat. A possible alignment tree for the running example alignment can be found in Figure 4.2.

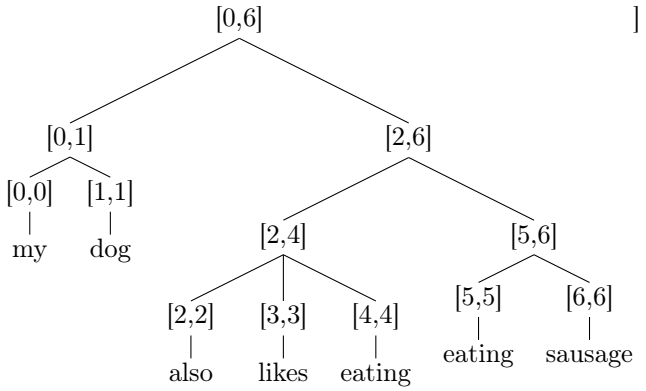

Figure 4.2: A possible alignment tree for the alignment of Figure 4.1

Figure 4.3: Example HAT, anders

Hierarchical Alignment Trees

HATs, as defined in Sima'an and Maillette de Buy Wenniger, are a strict subset of all alignment trees, in which all nodes have a minimal branching factor:

Definition 7. *A HAT is an alignment tree in which the fourth criterion is replaced by the following:*

4. *For every node* $[i, j] \in N$ *with children* $[x_1, y_1] \dots [x_n, y_n]$ *holds:* $x_k = y_{k-1} + 1$ *and* $\{x_1, \dots x_n, y_n\}$ *is a segmentation* B *of* $[i, j]$ *such that for all other segmentations* B' *of* $[i, j]$ *holds that* $|B'| \geq |B|$

Furthermore, the nodes of the HATs are decorated with ITG-like operators, that specify how the target-side HAT can be constructed. An example of a HAT can be found in Figure 4.3.

A HAT with operators uniquely determines a word-alignment, in a maximally recursive fashion. The latter is desirable, not only for practical reasons - it reduces the number of rules significantly - but mostly because it maximises the probability that we can generalise to new data. Sima'an and Maillette de Buy Wenniger provide empirical data, some of which were discussed in the previous section, describing what percentage of alignments can be explained by constrained versions of HATs.

The Power of HATs

If no constraints are imposed, HATs can describe *any* word alignment, which makes them a very powerful tool. To make this more precise, we will elaborate on two properties of the HATs that illustrate their generality.

Figure 4.4:

Figure 4.5: Non bijective mapping

Non isomorphic source and target structures. As the operators on the nodes of the HATs are set-permutations on their own, they can describe the existence of nodes in the target side structure that do not match precisly one source side node. This allows for a natural description of structures that cannot be described in the SCFG framework. Consider for instance the HAT showed in 4.4 for the translation of 'I don't smoke' into 'Je ne fume pas', that is problematic for SCFG's.

HATs describe a non-bijective mapping. From the non-isomorphism follows (anders) that the mapping between nodes in HATs is non-bijective, but the mapping between complete HATs is not necessarily bijective either, if the HATs are seen as (potentially labelled) structures.[3] To illustrate this, consider the following example of translation from English to Danish. The English sentences 'I give you flowers', and 'I give flowers to you' can both be translated into to the Danish 'Jeg giver dig blomster' (although 'jeg giver blomster til dig' would be a more appropriate translation for the second sentence, as it meets the criterion of being literal). In Figure 4.5, we see that the two linguistically plausible structures for the English sentences map to the same structure for the Danish sentence. As the two Danish sentences are identical, we may assume that if someone would assign labels to the nodes, the labels assigned to both trees would be identical as well, and hence we have established that the mapping between labelled structures is at least many-to-one. As the same argument holds in the other direction (i.e., both 'jeg giver blomster til dig' and 'Jeg giver dig blomster' can be found in the corpus as translation of 'I give you flowers'), from which we can conclude that the mapping between HATs can be in principle many-to-many. Clearly, when we take into account the operators as labels, the mapping is one-to-one.

In translation from English to Danish, this example is slightly artificial, as we normally require translations to be literal (anders). Nevertheless, examples like this might occur in corpora, and it is nice to see that HATs can in principle even account for small amounts of freedom during translation. Furthermore, examples like this might also occur in translation between languages that differ in the level of generality in expressing certain meanings. For instance, such a difference arises when the English word 'go' is translated into Russian, where it is required to specify whether you walked (идти) of used a vehicle (ехать), as a general verb that describes going from A to B does not exist in Russian.

[3] Maybe further explain in this footnote?

4.2.2 Experiments

Before describing our experiment, (anders) recall that the main aim of this paper is investigating the assumptions underpinning compositional translation. In particular, we want to see if it is possible to find recursive structures of sentences and a systematic mapping between them. The HATs are a very powerful tool for doing so, as they can describe any translation from source to target side. However, the mapping from word-alignments to HATs is a one-to-many mapping: a HAT uniquely describes a word-alignment, but a word alignment is often described by many HATs. To confirm that compositional translation is a reasonable strategy, we need somewhat stronger: a way of producing a single HAT for a word alignment, that is consistent over all sentences.[4] In this thesis we are concerned with finding such a consistent set of HATs for a corpus. There can be exponentially many HATs per sentence (compute how many?), and statistical learning this set without any external reference seems out of reach. Given that the nature of translation is preservation of the semantic content of a sentence, it seems reasonable to assume that the structural representation of a translation is semantically motivated. As guide in our search we will therefore use dependency parses (Schubert, 1987), that specify the predicate argument structure of a sentence as perceived by humans, hereby implicitly addressing the question: are predicate argument structures preserved during translation. As many previous empirical investigations, we will only focus on source side structures (at first), not worrying about the consistency of the target side structures they are mapped to, implying that we will not consider the node operators. If no consistent source side structures can be found, there is no hope for finding consistent pairs of structures.

Experiment 1

The predicate argument relations in a dependency tree, tell us exactly how the sentence is composed: we can infer which are the smaller parts of the sentence and how they are combined to obtain the complete sentence. Consider for instance the dependency tree of the sentence "My dog also likes eating sausage" (Figure 4.2.2).

The dependency tree tells us that 'likes' is the head word of the sentence, and that the sentences is composed of 4 parts: the head 'likes', its modifier 'also', its noun subject whose head is 'dog' and the open clausal complement whose head is 'eating'. The complement and subject are further divisible in, 'My' and 'dog', and 'eating' and 'sausage', respectively. Intuitively, for every relation in the dependency parse, we can check whether this relation exists in a HAT by

[4] There are two remarks needed to refine this statement. Firstly we assume that a sentence has only one meaning, ambiguity cases are thus ruled out. If a sentence has multiple meanings, different HATs might correspond to these meanings. This thesis considers such ambiguity aspects a separate problem, which (that?) is not taken into account here at all. Secondly, it is mainly theoretical that we want to fine *one* HAT per alignment. This is not to say, that in practice is might not be more desirable to generate multiple HATs per sentence over which a probability distribution can be defined. (anders)

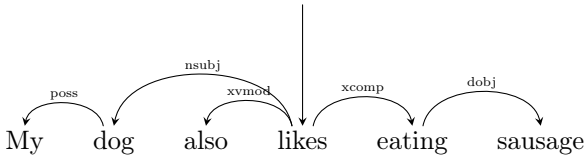

Figure 4.6: Stanford Dependency Tree

checking if the word and its depending subtrees are siblings in the HAT. In a first experiment, for every alignment, we will search for the HAT in which the number of dependency relations that is consistent with the HAT is the highest. We will assign a score to the HAT, proportional to the percentage of dependencies that is respected. A formal definition of this metric can be found in Appendix B. Note that relations within phrasal relations will always be consistent with the HATs, as words that are part of a phrasal translation are necessarily siblings, we thus do not need a special treatment to account for those.

Follow-up Experiments

In the best case, we can find a HAT for every sentence in which all dependency relations are preserved, but we suspect that this will not be so, in which cae we will further investigate if the result can be improved. We have distinguished five reasons that could lead to a low score:

1. The translation is erroneous, or non literal;
2. The dependency parse is erroneous;
3. The alignment is erroneous;
4. The structure of HATs and dependency parses does not agree
5. The sentence cannot be compositionally translated.

Empirical research like this using translation corpora hinge on the assumption that the datasets we use are representative for the phenomena we are investigating, and do not contain too many mistakes (anders). Unfortunately, this is often not the case. Dependency parsers are not perfect, the translations in our corpora are not always as literal as we would want them to be, and automatic alignments often contain many incorrect alignment links. Although these factors can play an important role, there is not much that we can do about it: we cannot instruct interpreters of the government to follow a protocol we like, and we do not have the manpower to filter our corpora or produce manual alignments for corpora of a reasonable size. Even in empirical research, testing the influence of these factors often boils down to manually checking the data. We will consider the influence of the alignments, by running the same experiments on manually aligned datasets.

As regards the first two causes, we might perform a manual analysis on a small subset of our data, but not before we have investigated the fourth case, which we consider likely to be an issue as we have forced our trees to be maximally recursive. Maximal recursivity is very useful for computational purposes, but is likely not the structure corresponding to human intuitions. We will illustrate this with two examples.

Firstly, consider the sentence 'I give you flowers', which contains one predicate ('give') with three arguments (the subject 'I', the object 'flowers' and the indirect object 'you'). Its Dutch translation 'Ik geef jou bloemen' has exactly the same predicate argument structure *and* word-order, whereby the branching factor in any of its HATs will not exceed two. However, a maximum score can only be obtained by a tree in which 'I', 'give', 'you', and 'flowers' are siblings, whose mother will have a branching factor of (at least) four. Even though the translation of this sentence seems perfectly compositional, no HAT will thus obtain the maximum score, because the dependency structure is not minimally branching.

A second example, that is more related to translational divergence, arises when two arguments are translated into one (which happens when, e.g., arguments are translated are pre- or suffixes, verbs do not require a subject or when spaces). Consider for instance the sentence 'Can you give me the salt' and its Italian translation 'puoi passarmi il sale'. Once again, the predicate-argument structure of the sentence is well preserved. However, the dependency parse prescribes that 'the salt', 'can' and 'you' should be siblings of 'give', which will be the case in none of the HATs over $\{\{0\},\{0\},\{1\},\{1\},\{2\},\{3\}\}$, as 'give' and 'me' are together translated into 'passarmi', and 'can you' into 'puoi'.

Both cases could be solved when considering dependency motivated labels, similar to the ones defined in Zollmann and Venugopal (2006), that represent compound categories, which we will do in a second experiment (e.g., 'give you flowers' could be seen as a sentence missing a subject to the left (subj\S) and 'I give' as a combination of a subject and a verb (subj+verb)). We will investigate these new labels by obtaining some statistical details about how often they are translation units in the alignments (anders). Subsequently, we will rescore the HATs with the new labels, slightly adapting the scoring metric. Instead of looking at sibling relations, we will just consider how many of the nodes in the HAT can be labelled using a label from our new label set. A HAT will receive a score corresponding with the percentage its nodes that could be labelled and thus receives a maximum score if all of its nodes could be labelled. Note that this introduces a slight bias towards trees with more nodes: a tree with 10 nodes of which one is unlabelled receives a higher score than a tree with 9 nodes of which one is unlabelled.

Chapter 5

Results

This chapter will describe the sequence of experiments we conducted, as well as their results. Implementation details can be found in A.

Chapter 6

Discussion and Future Work

short summary of findings and what they mean

Chapter 7

Conclusion

Appendix A

Implementation

NLTK toolkit: Bird et al. (2009)
Stanford Dependency Parser: De Marneffe and Manning (2008)(?)

Appendix B

Metrics

B.1 Notation

Firstly, we will present some notation that is shared along the different metrics.

Notion 1. T_d will refer to a dependency tree of a sentence $s = w_1 \dots w_n$, formed by a set of dependencies $D = \{(i,j)|$ there is a dependency arrow from word w_i to word $w_j\}$.

Notion 2. If T_d is a dependency tree for s, w is a word in s and i and j are the maximum and minimum positions, respectively, that can be reached from w by following the directed dependency arrows. Then span$(w) = [i,j]$.

Notion 3. T_a will be used to refer to an alignment tree of a sentence $s = w_1 \dots w_n$. The label $i-j$ will refer to the node that dominates span $[i,j]$. The highest node of T_a will be denoted with N_{T_a}

Notion 4. Let T_d be a dependency tree with dependencies D, Then $D' = \{(i, \text{span}(j)) \mid D(i,j) \wedge 1 \leq i,j \leq n\}$ is the set in which each dependent is replaced by its span.

Notion 5. If N is a node in a tree T_a, C_N denotes the set of child constituents of this node. If node N dominates words i to j in s, then $dom(N) = [i,j]$

B.2 Metric 1

Metric 1. Let $s = w_1 w_2 \dots w_n$ be a sentence, and T_d and T_a its dependency tree and an alignment tree, respectively. The score of T_a is defined as the score of its highest node N_a:

$$E(N_a, D) = \sum_{c \in C_{N_a}} E(c, D) + \sum_{c_1 \in C_{N_a}} \sum_{c_2 \in C_{N_a}} B(c_1, c_2)$$

With base case $E(N, D) = 0$ and $B(c_1, c_2) = 1$ iff $(c_1, c_2) \in D'$. Dividing the resulting score by $|D'|$ will result in a normalized score.

Note if this definition is strictly followed more than half of the sibling checks is redundant, an algorithm computing the score of a tree would not have to perform them all.

B.3 Metric 2

Metric 2. Let $s = w_1 w_2 \dots w_n$ be a sentence, and T_d and T_a its dependency tree and an alignment tree, respectively. The score of T_a is defined as the score of its highest node N_a:

$$E(N_a, D) = \sum_{c \in C_{N_a}} E(c, D) + \sum_{c_1 \in C_{N_a}} \sum_{c_2 \in C_{N_a}} B(c_1, c_2)$$

With base case $E(N, D) = 0$ and $B(c_1, c_2) = 1$ iff $|dom(c_2)| > 1 \wedge (c_1, c_2) \in D'$ the part of the sentence covered by c_2. Dividing the resulting score by $|D'|$ will result in a normalized score.

Note that normalizing the score will sometimes result in zero division for shorter sentences whose dependency parses display no compositional structure, in this cases we will define the score of the sentence to be 0.

B.3.1 Metric 1

B.3.2 Metric 2

Explain that metric 1 reflects the similarity with the dependency parse, rather than giving a reasonable measure of compositionality. Explain why this is, that a part of the score can trivially be reached by just making a flat tree. Explain how to fix this. Explain that evaluation metric 2 won't alter the ordering of the trees, just their scores. Explain that metric 2 thus just differs in the set of relations it considers: instead of considering all relations from the dependency parse, it only considers the relations that reflect compositionality, which captures the intuition that completely flat trees should be assigned a 0 score. Note that this means that this therefore does not alter the ranking of the trees set by metric 1, it just alters the scores associated with the trees.

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