Final Report

of the

2006 Language Engineering Workshop

Open Source Toolkit for Statistical Machine Translation:

Factored Translation Models and Confusion Network Decoding

`http://www.clsp.jhu.edu/ws2006/groups/ossmt/`

`http://www.statmt.org/moses/`

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Abstract

The 2006 Language Engineering Workshop *Open Source Toolkit for Statistical Machine Translation* had the objective to advance the current state-of-the-art in statistical machine translation through richer input and richer annotation of the training data. The workshop focused on three topics: factored translation models, confusion network decoding, and the development of an open source toolkit that incorporates this advancements.

This report describes the scientific goals, the novel methods, and experimental results of the workshop. It also documents details of the implementation of the open source toolkit.

Acknowledgments

The participants at the workshop would like to thank everybody at Johns Hopkins University who made the summer workshop such a memorable — and in our view very successful — event. The JHU Summer Workshop is a great venue to bring together researchers from various backgrounds and focus their minds on a problem, leading to intense collaboration that would not have been possible otherwise.

We especially would like to thank Fred Jelinek for heading the Summer School effort and Laura Graham and Sue Porterfield for keeping us sane during the hot summer weeks in Baltimore.

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Chapter 1

Introduction

Statistical machine translation has emerged as the dominant paradigm in machine translation research. Statistical machine translation is built on the insight that many translation choices have to be weighed against each other — whether it is different ways of translating an ambiguous word, or alternative ways of reordering the words in an input sentence to reflect the target language word order. In statistical machine translation these choices are guided using probabilities which are estimated using collections of translated texts, called parallel corpora.

While statistical machine translation research has gained much by building on the insight that probabilities may be used to make informed choices, current models are deficient because they lack crucial information. Much of the translation process is best explained with morphological, syntactic, semantic, or other information that is not typically contained in parallel corpora. We show that when such information is incorporated to the training data, we can build richer models of translation, which we call **factored translation models**. Since we automatically tag our data there often many ways of marking up input sentences. This further increases multitude of choices that our machine translation must deal with, and requires an efficient method for dealing with potentially ambiguous input. We investigate **confusion network decoding** as a way of addressing this challenge.

In addition to these scientific goals, we also address another pervasive problem for our field. Given that the methods and systems we develop are increasingly complex, simply catching up with the state-of-the-art has become a major part of the work done by research groups. To reduce this tremendous duplication of efforts, we have made our work available in an **open source toolkit**. To this end, we merged the efforts of a number of research labs (University of Edinburgh, ITC-irst, MIT, University of Maryland, RWTH Aachen) into a common set of tools, which includes the core of a machine translation system: the decoder. This report documents this effort, which we have continued to pursue beyond the summer workshop.

1.1 Factored Translation Models

We are proposing a new approach that we call factored translation models, which extends traditional phrase-based statistical machine translation models to take advantage from additional annotation, especially linguistic markup. Phrase-based statistical machine translation is a very strong baseline to improve upon. Phrase-based systems have consistently outperformed other methods in recent competitions. Any improvements over this approach therefore implies an improvement in the state-of-the-art.

The basic idea behind factored translation models is to represent phrases not simply as sequences of fully inflected words, but instead as sequences containing multiple levels of information. A word in our model is not a single token, but vector of factors. This enables straight-forward integration of part-of-speech tags, morphological information, and even shallow syntax. Instead of dealing with linguistic markup in preprocessing or postprocessing steps (e.g., the re-ranking approaches of the 2003 JHU workshop), we build a system that intergrate this information into the decoding process to better guide the search.

Our approach to factored translation models is described in detail in Chapter 2. The results of the experiments that we conducted on factored translation between English and German, Spanish and Czech are given in Chapter 3.

1.2 Confusion Network Decoding

With the move to factored translation models, there are now several reasons why we may have to deal with ambiguous input. One is that the tools that we use to annotated our data may not make deterministic decisions. Instead of only relying on the 1-best output of our tools, we accept ambiguous input in the form of confusion networks. This preserves ambiguity and defers firm decisions until later stages, which has been shown to be advantageous in previous research.

While confusion networks are a useful way of dealing with ambiguous factors, they are more commonly used to represent the output of automatic speech recognition when combining machine translation and speech recognition in speech translation systems. Our approach to confusion network decoding, and its application to speech translation, is described in detail in Chapter 4. Chapter 5 presents experimental results using confusion networks.

1.3 Open Source Toolkit

There are several reasons to create an open research environment by opening up resources (tools and corpora) freely to the wider community. Since our research is largely publicly funded, it seems appropriate to return the products of this work to the public. Access to free resources enables other research group to advance work that was started here, and provides them with baseline performance results for their own novel efforts.

While these are honorable goals, our motivation for creating this toolkit is also somewhat self-interested: Building statistical machine translation systems has become a very complex task, and rapid progress in the field forces us to spend much time reimplementing other researchers' advances in our system. By bringing several research groups together to work on the same system, this duplication of effort is reduced and we can spend more time on what we would really like to do: Come up with new ideas and test them.

The starting point of the Moses system was the Pharaoh system of the University of Edinburgh [Koehn, 2004]. It was re-engineered during the workshop, and several major new components were added. Moses is a full-fledged statistical machine translation system, including the training, tuning and decoding components. The system provides state-of-the-art performance out of the box, as has been shown at recent ACL-WMT [Callison-Burch et al., 2007], TC-STAR, and IWSLT [Shen et al., 2006] evaluation campaigns.

The implementation and usage of the toolkit is described in more detail in Chapter 6.

Chapter 2

Factored Translation Models

The current state-of-the-art approach to statistical machine translation, so-called phrase-based models, represent phrases as sequences of words without any explicit use of linguistic information, be it morphological, syntactic, or semantic. Such information has been shown to be valuable when it is integrated into pre-processing or post-processing steps. For instance, improvements in translation quality have been achieved by preprocessing Arabic morphology through stemming or splitting off of affixes that typically translate into individual words in English [Habash and Rambow, 2005]. Other research shows the benefits of reordering words in German sentences prior to translation so that their word order is more similar to English word order [Collins et al., 2005].

However, a tighter integration of linguistic information into the translation model is desirable for two reasons:

- Translation models that operate on more general representations, such as lemmas instead of surface forms of words, can draw on richer statistics and overcome data sparseness problems caused by limited training data.

- Many aspects of translation can be best explained on a morphological, syntactic, or semantic level. Having such information available to the translation model allows the direct modeling of these aspects. For instance: reordering at the sentence level is mostly driven by general syntactic principles, local agreement constraints show up in morphology, etc.

Therefore, we developed a framework for statistical translation models that tightly integrates additional information. Our framework is an extension of phrase-based machine translation [Och, 2002].

2.1 Current Phrase-Based Models

Current phrase-based models of statistical machine translation [Och, 2002; Koehn et al., 2003] are based on on earlier word-based models [Brown et al., 1988, 1993] that define the translation model probability $P(\mathbf{f}|\mathbf{e})$ in terms of word-level alignments $\mathbf{a}$.

$$P(\mathbf{f}|\mathbf{e}) = \sum_{a} P(\mathbf{a}, \mathbf{f}|\mathbf{e}) \tag{2.1}$$

Brown et al. [1993] introduced a series of models, referred to as the IBM Models, which defined the alignment probability $P(\mathbf{a}, \mathbf{f}|\mathbf{e})$ so that its parameters could be estimated from a parallel corpus using expectation maximization.

Phrase-based statistical machine translation uses the IBM Models to create high probability word-alignments, such as those shown in Figure 2.1, for each sentence pair in a parallel corpus.

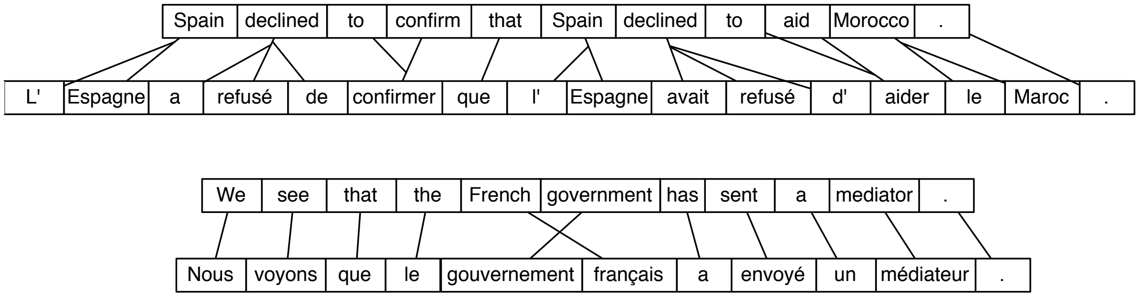
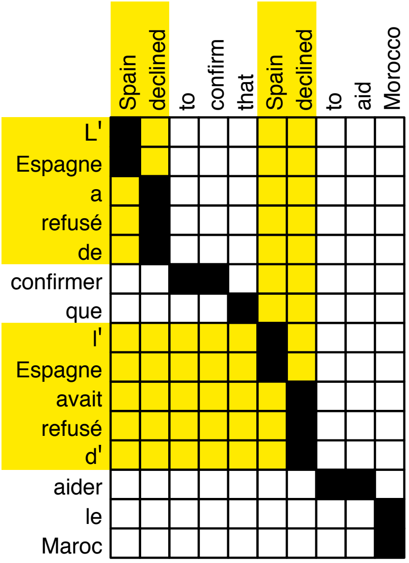

Spain declined to confirm that Spain declined to aid Morocco .
L' Espagne a refusé de confirmer que l' Espagne avait refusé d' aider le Maroc .
We see that the French government has sent a mediator .
Nous voyons que le gouvernement français a envoyé un médiateur .

Figure 2.1: Word-level alignments are generated for sentence pairs using the IBM Models.



L' Espagne	Spain
L' Espagne a refusé de	Spain declined
L' Espagne a refusé de confirmer	Spain declined to confirm
a refusé de	declined
a refusé de confirmer	declined to confirm
a refusé de confirmer que	declined to confirm that
confirmer	to confirm
confirmer que	to confirm that
que	that
que l' Espagne	that Spain
que l' Espagne avait refusé d'	that Spain declined
l' Espagne	Spain
l' Espagne avait refusé d'	Spain declined
l' Espagne avait refusé d' aider	Spain declined to aid
...	...

Figure 2.2: Phrase-to-phrase correspondences are enumerated from word-level alignments.

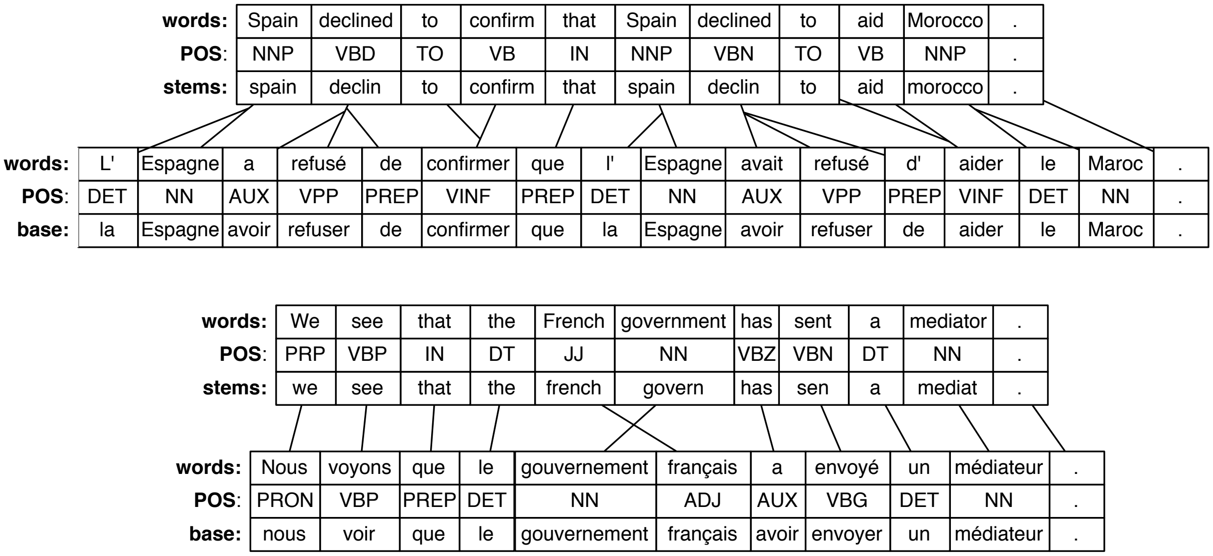
All phrase-level alignments that are consistent with the word-level alignments are then enumerated using phrase-extraction techniques [Marcu and Wong, 2002; Koehn et al., 2003; Tillmann, 2003; Venugopal et al., 2003]. This is illustrated in Figure 2.2. The highlighted regions show how two French translations of the English phrase *Spain declined* can be extracted using the word alignment. Once they have been enumerated these phrase-level alignments are used to estimate a *phrase translation probability*, $p(\bar{f}|\bar{e})$, between a foreign phrase $\bar{f}$ and English phrase $\bar{e}$. This probability is generally estimated using maximum likelihood as

$$p(\bar{f}|\bar{e}) = \frac{count(\bar{f},\bar{e})}{count(\bar{e})} \tag{2.2}$$

The phrase translation probability is integrated into a log linear formulation of translation [Och and Ney, 2002]. The log linear formulation of translation is given by

$$P(\mathbf{e}|\mathbf{f}) = \exp\sum_{i=1}^{n}\lambda_i h_i(\mathbf{e},\mathbf{f}) \tag{2.3}$$

Where h_i can be an arbitrary *feature function* that assigns a score to a translation. Commonly used feature functions include the phrase translation probability, and also trigram language model probabilities, word translation probabilities, phrase length penalty, and reordering costs.



words:	Spain	declined	to	confirm	that	Spain	declined	to	aid	Morocco	.
POS:	NNP	VBD	TO	VB	IN	NNP	VBN	TO	VB	NNP	.
stems:	spain	declin	to	confirm	that	spain	declin	to	aid	morocco	.

words:	L'	Espagne	a	refusé	de	confirmer	que	l'	Espagne	avait	refusé	d'	aider	le	Maroc	.
POS:	DET	NN	AUX	VPP	PREP	VINF	PREP	DET	NN	AUX	VPP	PREP	VINF	DET	NN	.
base:	la	Espagne	avoir	refuser	de	confirmer	que	la	Espagne	avoir	refuser	de	aider	le	Maroc	.

words:	We	see	that	the	French	government	has	sent	a	mediator	.
POS:	PRP	VBP	IN	DT	JJ	NN	VBZ	VBN	DT	NN	.
stems:	we	see	that	the	french	govern	has	sen	a	mediat	.

words:	Nous	voyons	que	le	gouvernement	français	a	envoyé	un	médiateur	.
POS:	PRON	VBP	PREP	DET	NN	ADJ	AUX	VBG	DET	NN	.
base:	nous	voir	que	le	gouvernement	français	avoir	envoyer	un	médiateur	.

Figure 2.3: Factored Translation Models integrate multiple levels of information in the training data.

2.1.1 Problems with phrase-based models

The limitations of current approaches to statistical machine translation stem from their formulation of phrases. Because they treat phrases as sequences of fully-inflected words and do not incorporate any additional linguistic information, they are limited in the following ways:

- They are unable to learn translations of words that do not occur in the data, because they are unable to generalize. Current approaches know nothing of morphology, and fail to connect different word forms. When a form of a word does not occur in the training data, current systems are unable to translate it. This problem is severe for languages which are highly inflective, and in cases where only small amounts of training data are available.

- They are unable to distinguish between different linguistic contexts. When current models have learned multiple possible translations for a particular word or phrase, the choice of which translation to use is guided by frequency information rather than by linguistic information. Often times linguistic factors like case, tense, or agreement are important determinants for what translation ought to be used in a particular context. Because current phrase-based approaches lack linguistic information they do not have an appropriate means of choosing between alternative translations.

- They have limited capacities for learning linguistic facts. Because current models do not use any level of abstraction above words, it is impossible to model simple linguistic facts. Under current approaches it is impossible to learn or to explicitly specify that adjective-noun alternation occurs between two languages, or that a language's word order is subject-object-verb, or similar linguistic facts.

2.2 Factored Translation Models

We propose Factored Translation Models to advance statistical machine translation through the incorporation multiple levels of information. These layers of information, or *factors*, are integrated into both the training data and the models. The parallel corpora used to train

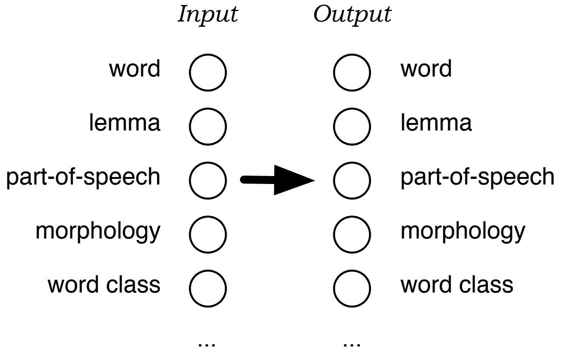


Figure 2.4: The models specify a mapping between factors in the source and target languages. In this report we represent different model configurations by showing which factors are connected using arrows.

Factored Translation Models are tagged with factors such as parts of speech and lemmas, as shown in Figure 2.3. Instead of modeling translation between full inflected words in the source and targets, our models can incorporate more general mappings between factors in the source and target (and between factors within the target, as well shall shortly discuss). We can represent different models graphically by showing the mappings between the different factors, by adding connecting lines in Figure 2.4.

The use of factors introduces several advantages over current phrase-based approaches:

- Morphology can be better handled by translating in multiple steps.
- Linguistic context can facilitate better decisions when selecting among translations.
- Linguistic mark up of the training data allows for many new modeling possibilities.

2.2.1 Better handling of morphology

One example of the short-comings of the traditional surface word approach in statistical machine translation is the poor handling of morphology. Each word form is treated as a token in itself. This means that the translation model treats, say, the word *house* as completely independent of the word *houses*. Any instance of *house* in the training data does not add any knowledge to the translation of *houses*.

In the extreme case, while the translation of *house* may be known to the model, the word *houses* may be unknown and the system will not be able to translate it. While this problem does not show up as strongly in English — due to the very limited morphological production in English — it does constitute a significant problem for morphologically rich languages such as Arabic, German, Czech, etc.

Thus, it may be preferable to model translation between morphologically rich languages on the level of lemmas, and thus pooling the evidence for different word forms that derive from a common lemma. In such a model, we would want to translate lemma and morphological information separately,[1] and combine this information on the target side to generate the ultimate output surface words. Such a model, which makes more efficient use of the translation lexicon, can be defined as a factored translation model as illustrated in Figure 2.5.

[1] Note that while we illustrate the use of factored translation models on such a linguistically motivated example, our framework can be equally well applied to models that incorporate automatically defined word classes.

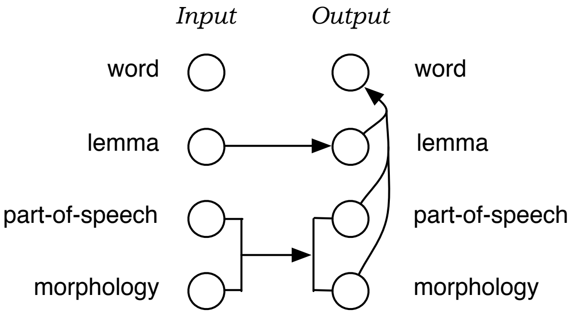


Figure 2.5: A particular configuration of a factored translation model which employs *translation steps* between lemmas and POS+morphology, and a *generation step* from the POS+morphology and lemma to the fully inflected word

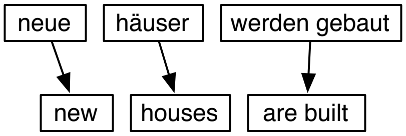
Translation and Generation Steps

The translation of the factored representation of source words into the factored representation of target words is broken up into a sequence of **mapping steps** that either **translate** input factors into output factors, or **generate** additional target factors from existing target factors.

The previous of a factored model which uses morphological analysis and generation breaks up the translation process into the following steps:

- Translating morphological and syntactic factors
- Generating surface forms given the lemma and linguistic factors

Factored translation models build on the phrase-based approach, which divides a sentence into small text chunks (so-called phrases) and translates those chunks. This model implicitly defines a segmentation of the input and output sentences into such phrases, such as:



Our current implementation of factored translation models strictly follows the phrase-based approach, with the additional decomposition of phrase translation into a sequence of mapping steps. Since all mapping steps operate on the same phrase segmentation of the input and output sentence into phrase pairs, we call these **synchronous factored models**.

Let us now take a closer look at one example, the translation of the one-word phrase *häuser* into English. The representation of *häuser* in German is: surface-form *häuser*, lemma *haus*, part-of-speech *NN*, count *plural*, case *nominative*, gender *neutral*.

Given the three mapping steps in our morphological analysis and generation model may provide the following applicable mappings:

- **Translation:** Mapping lemmas
  - *haus* → *house, home, building, shell*
- **Translation:** Mapping morphology
  - *NN*|*plural-nominative-neutral* → *NN*|*plural, NN*|*singular*

- **Generation:** Generating surface forms
  - *house|NN|plural* → *houses*
  - *house|NN|singular* → *house*
  - *home|NN|plural* → *homes*
  - *...*

The German *haus|NN|plural|nominative|neutral* is expanded as follows:

- **Translation:** Mapping lemmas
  { *?|house|?|?, ?|home|?|?, ?|building|?|?, ?|shell|?|?* }
- **Translation:** Mapping morphology
  { *?|house|NN|plural, ?|home|NN|plural, ?|building|NN|plural, ?|shell|NN|plural, ?|house|NN|singular, ...* }
- **Generation:** Generating surface forms
  { *houses|house|NN|plural, homes|home|NN|plural, buildings|building|NN|plural, shells|shell|NN|plural, house|house|NN|singular, ...* }

These steps are not limited to single words, but instead can be applied to sequences of factors. Moreover, each of these steps has a probabilistic definition. Just as phrase-based models calculate phrase translation probabilities $p(\bar{e}_{words}|\bar{f}_{words})$ over fully inflected words, factored translation models use probabilities over more abstract features, such as $p(\bar{e}_{lemma}|\bar{f}_{lemma})$ and $p(\bar{e}_{morph+pos}|\bar{f}_{morph+pos})$. The generation steps can also be defined probabilistically as $p(\bar{e}_{words}|\bar{e}_{lemma}, \bar{e}_{morph+pos})$. As in phrase-based models, the different components of the model are combined in a log-linear model. In addition to traditional components — language model, reordering model, word and phrase count, etc. — each translation and generation probability is represented by a feature in the log linear model.

2.2.2 Adding context to facilitate better decisions

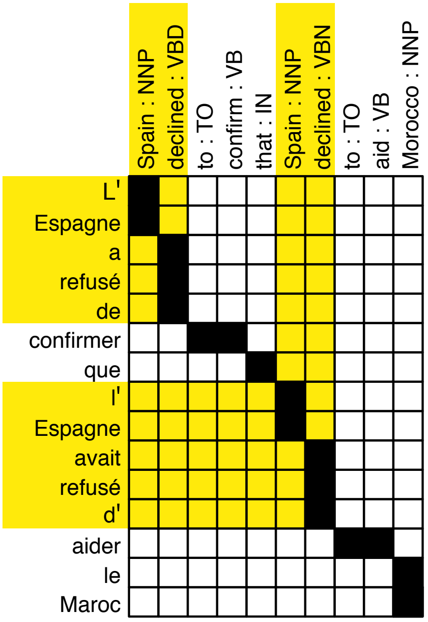
If the only occurrences of *Spain declined* occurred in the sentence pair given in Figure 2.1, the phrase translation probability for the two French phrases under current phrase-based models would be

$$\begin{aligned} p(\textit{l' Espagne a refusé de}|\textit{Spain declined}) &= 0.5 \\ p(\textit{l' Espagne avait refusé d'}|\textit{Spain declined}) &= 0.5 \end{aligned}$$

Under these circumstances the two forms of *avoir* would be equiprobable and the model would have no mechanism for choosing between them. In Factored Translation Models translation probabilities can be conditioned on more information than just words. For instance, using the combination of factors given in Figure 2.6 we can calculate translation probabilities that are conditioned on both words and parts of speech

$$p(\bar{f}_{words}|\bar{e}_{words}, \bar{e}_{pos}) = \frac{count(\bar{f}_{words}, \bar{e}_{words}, \bar{e}_{pos})}{count(\bar{e}_{words}, \bar{e}_{pos})} \tag{2.4}$$

Whereas in the conventional phrase-based models the two French translations of *Spain declined* were equiprobable, we now have a way of distinguishing between them. We can now correctly



L' Espagne	Spain, NNP
L' Espagne a refusé de	Spain declined, NNP VBD
a refusé de	declined, VBD
a refusé de confirmer	declined to confirm, VBD TO VB
confirmer	to confirm, TO VB
confirmer que	to confirm that, TO VB IN
que	that, IN
que l' Espagne	that Spain, IN NNP
que l' Espagne avait refusé d'	that Spain declined, IN NNP VBN
l' Espagne	Spain, NNP
l' Espagne avait refusé d'	Spain declined, NNP VBN
l' Espagne avait refusé d' aider	Spain declined to aid, NNP VBN TO VB
avait refusé d'	declined to, VBN TO
avait refusé d' aider	declined to aid, VBN TO
VB	
...	...

Figure 2.6: Different factors can be combined. This has the effect of giving different conditioning variables.

choose which form of *avoir* to use if we know that the English verb *decline* is past tense (VBD) or that it is a past participle (VBN):

$$\begin{aligned} p(\textit{l' Espagne a refusé de}|\textit{Spain declined, NNP VBN}) &= 0 \\ p(\textit{l' Espagne avait refusé d'}|\textit{Spain declined, NNP VBN}) &= 1 \end{aligned}$$

$$\begin{aligned} p(\textit{l' Espagne a refusé de}|\textit{Spain declined, NNP VBD}) &= 1 \\ p(\textit{l' Espagne avait refusé d'}|\textit{Spain declined, NNP VBD}) &= 0 \end{aligned}$$

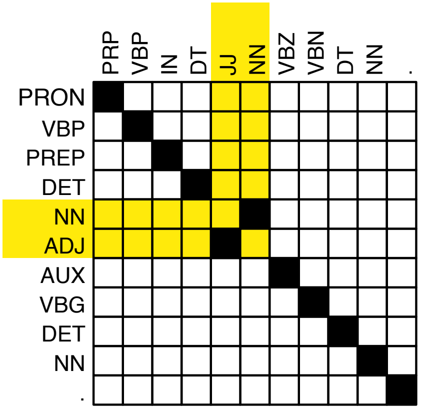
2.2.3 New modeling possibilities

The introduction of factors also allows us to model things we were unable to model in the standard phrase-based approaches to translation. For instance, we can now incorporate a translation model probability which operates over sequences of parts of speech, $p(\bar{f}_{pos}|\bar{e}_{pos})$. We can estimate these probabilities straightforwardly using techniques similar to the ones used for phrase extraction in current approaches to statistical machine translation. In addition to enumerating phrase-to-phrase correspondences using word alignments, we can also enumerate POS-to-POS correspondences, as illustrated in Figure 2.7. After enumerating all POS-to-POS correspondences for every sentence pair in the corpus, we can calculate $p(\bar{f}_{pos}|\bar{e}_{pos})$ using maximum likelihood estimation

$$p(\bar{f}_{pos}|\bar{e}_{pos}) = \frac{count(\bar{f}_{pos}, \bar{e}_{pos})}{count(\bar{e}_{pos})} \tag{2.5}$$

This allows us to capture linguistic facts within our probabilistic framework. For instance, the adjective-noun alternation that occurs between French and English would be captured because the model would assign probabilities such that

$$p(\text{NN ADJ}|\text{JJ NN}) > p(\text{ADJ NN}|\text{JJ NN})$$



PRON	PRP
PRON VBP	PRP VBP
PRON VBP PREP	PRP VBP IN
PRON VBP PREP DET	PRP VBP IN DT
VBP	VBP
VBP PREP	VBP IN
VBP PREP DET	VBP IN DT
...	...
NN ADJ	JJ NN
NN ADJ AUX	JJ NN VBZ
NN ADJ AUX VBG	JJ NN VBZ VBN
...	...

Figure 2.7: In factored models correspondences between part of speech tag sequences are enumerated in a similar fashion to phrase-to-phrase correspondences in standard models.

Thus a simple linguistic generalization that current approaches cannot learn can be straightforwardly encoded in Factored Translation Models.

Moreover, part of speech tag sequences are not only useful for calculating translation probabilities such as $p(\bar{f}_{pos}|\bar{e}_{pos})$. They may also be used for calculating "language model" probabilities such as $p(\bar{f}_{pos})$. The probability $p(\bar{f}_{pos})$ can be calculated similarly to the n-gram language model probability $p(\bar{f}_{words})$, which is used in current statistical machine translation systems. Sequences of parts of speech have much richer counts than sequences of words since the number of unique part of speech tags is much smaller than the number of unique words. This allows higher order n-gram models to be estimated from data. Practical constraints generally limit us to tri-gram language models over words, but we can accurately estimate 6- or 7-gram language models over parts of speech.

2.3 Statistical Modeling

Factored translation models closely follow the statistical modeling methods used in phrase-based models. Each of the mapping steps is modeled by a feature function. This function is learned from the training data, resulting in translation tables and generation tables.

Phrase-based statistical translation models are acquired from word-aligned parallel corpora by extracting all phrase-pairs that are consistent with the word alignment. Given the set of extracted phrase pairs with counts, various scoring functions are estimated, such as conditional phrase translation probabilities based on relative frequency estimation.

Factored models are also acquired from word-aligned parallel corpora. The tables for translation steps are extracted in the same way as phrase translation tables. The tables for generation steps are estimated on the target side only (the word alignment plays no role here, and additional monolingual data may be used). Multiple scoring functions may be used for generation and translation steps, in our experiments we used

- five scores for translation steps: conditional phrase translation probabilities in both direction (foreign to English and vice versa), lexical translation probabilities (foreign to English and vice versa), and phrase count;
- two scores for generation steps: conditional generation probabilities in both directions (new target factors given existing target factors and vice versa).

The different components of the model are combined in the log-linear model. In addition to traditional components — language model, reordering model, word and phrase count, etc. — each mapping step forms a component with five (translation) or two (generation) features. The feature weights in the log-linear model are determined using a minimum error rate training method [Och, 2003].

2.4 Efficient Decoding

Compared to phrase-based models, the decomposition of the phrase translation into several mapping steps creates additional computational complexity. Instead of a simple table lookup to obtain the possible translation for an input phrase, now a sequence of such tables have to be consulted and their content combined.

Since all translation steps operate on the same segmentation, the **expansion** of these mapping steps can be efficiently pre-computed prior to the heuristic beam search, and stored as translation options (recall the example in Section 2.2.1, where we carried out the expansion for one input phrase). This means that the fundamental search algorithm does not change. Only the scoring of hypothesis becomes slightly more complex.

However, we need to be careful about the combinatorial explosion of the number of translation options given a sequence of mapping steps. If one or many mapping steps result in a vast increase of (intermediate) expansions, this may be become unmanageable. We currently address this problem by early pruning of expansions, and limiting the number of translation options per input phrase to a maximum number, by default 50.

2.5 Current Shortcomings

One significant limiting factor in the performance of multi-factored translation models is the due to the present requirement that successive translation steps all translate identical source and target spans. If a compatible translation is not found for a secondary translation step (either because hypotheses with compatible factors were discarded earlier or because there is no possible translation in the phrase table for the secondary translation step), the hypothesis is abandoned. This has considerable benefit from a computational perspective since it constrains the search space for potential targets when translating secondary factors. However, it causes a number of significant problems:

1. In models where a secondary factor is both generated from another target factor and translated from a source factor, any pruning before both steps have completed runs the risk of producing not just degraded output, but failing to find any adequate translation.

2. Because a compatible translation must be found in secondary steps for a translation hypothesis to survive, it is difficult to filter secondary translation tables. This results in very large tables which are inefficient to load and have considerable memory overhead.

3. When secondary translation steps fail and hypotheses are abandoned, the model is forced to rely on shorter translation units for the primary translation step. This is in direct conflict to the potential benefits that can be gained by richer statistics.

There are several possible ways that the exact-span match requirement might be addressed. One solution that is computationally tractable is to back off to shorter spans only in the event of a failure to find any possible translation candidates during subsequent translation steps. The problem that arises is how the spans established should be translated once multiple translation units can be used. Reordering within phrases is certainly quite common. These can be further constrained to either match alignments that are suggested by the initial span.

Chapter 3

Experiments with Factored Translation Models

This chapter reviews the factored translation model experiments conducted at the summer workshop. After developing the Moses software during the workshop, we used it to create different configurations of factored translation models to address particular problematic cases when translating into different languages. The structure of this chapter is as follows:

- Section 3.1 presents our experiments for translation from English into German. We configured factored models to address German morphology through lemmas, and to integrate part of speech and agreement information to improve grammatical coherence.
- Section 3.2 describes factored models for translation from English into Spanish, where Spanish subject-verb and adjective-noun-determiner agreement is explicitly modeled. These experiments further examine how factored models can be used to improve translation quality in small data scenarios.
- Section 3.3 compares the performance of three different English to Czech translation models with include lemma and morphological information as factors, and shows that these models result in better translation quality than the baseline phrase-based model.

3.1 English-German

German is an example for a language with a relatively rich morphology. Historically, most research in statistical machine translation has been carried out on language pairs with the target language English.

This leads to the question: Does rich morphology pose problems that have not been addressed so far, if it occurs on the target side? Previous research has shown, that stemming morphologically rich input languages leads to better performance. However, this trick does not work when we have to *generate* rich morphology.

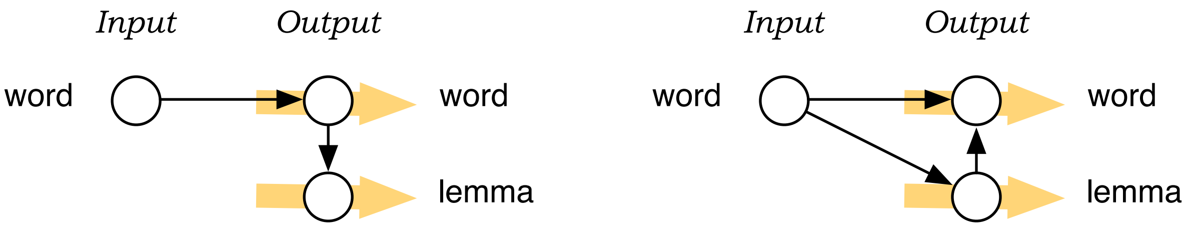
3.1.1 Impact of morphological complexity

To assess the impact of rich morphology, we carried out a study to see what performance gains could be achieved, if we could generate German morphology perfectlty.

For this, we used a translation model trained on 700,000 sentences of the English–German Europarl corpus (a training corpus we will work throughout this section), and the test sets taken from the 2006 ACL Workshop of Statistical Machine Translation. We trained a system with the standard settings of the Moses system (described in 6).

Method	devtest	test
BLEU measured on words	17.76	17.80
BLEU measured on stems	21.70	21.47

Table 3.1: Assessment of what could be gained with perfect morphology: BLEU scores measured on the word leveled on on stemmed system output and reference sets. The BLEU score decreases by 4 points due to errors in the morphology.



Lemma Model 1

Lemma Model 2

Figure 3.1: Two models for including lemmas in factored translation models: Both models map words from input to output in a translation step and generate the lemma on the output side. Model 2 includes an additional step that maps input words to output lemmas.

English–German is a difficult language pair, which is also reflected in the BLEU scores for this task. For our setup, we achieved a score of 17.80 on the 2006 test set, whereas for other language pairs scores of over 30 BLEU can be achieved. How much of this is due to the morphological complexity of German? If we measure BLEU not on words (as it typically done), but on stems, we can get some idea how to answer this question. As shown in Table 3.1 the stem-BLEU score is 21.47, almost 4 points higher.

One of the motivations for the introduction of factored translation models is the problem of rich morphology. Morphology increases the vocabulary size and leads to sparse data problems. We expect that backing off to word representations with richer statistics such as stems or word classes will allow us to deal with this problem. Also, morphology carries information about grammatical information such as case, gender, and number, and by explicitly expressing this information in form of factors will allow us to develop models that take grammatical constraints into account.

3.1.2 Addressing data sparseness with lemmas

The German language model may not be as effectives in machine translation as language models are for English, since its rich morphology fragments the data. This raises the question whether this problem of data sparseness may be overcome by building a language model on lemmas instead of the surface form of words.

To test this hypothesis, we build two factored translation models, as illustrated in Figure 3.1. The models are based on traditional phrase-based statistical machine translation systems, but add additional information in form of lemmas on the output side which allows the integration of a language model trained on lemmas. Note that this goes beyond previous work in reranking, since the second language model trained on lemmas is integrated into the search.

In our experiments, we obtained higher translation performance when using the factored translation models that integrate a lemma language models (all language models are trigram

Method	devtest	test
baseline	18.22	18.04
hidden lemma (gen only)	**18.82**	**18.69**
hidden lemma (gen and trans)	18.41	18.52
best published results	-	18.15

Table 3.2: Results with the factored translation models integrating lemmas from Figure 3.1: language models over lemmas lead to better performance, beating the best published results. Note: the baseline presented here is higher than the one used in Table 3.1, since we used a more mature version of our translation system.

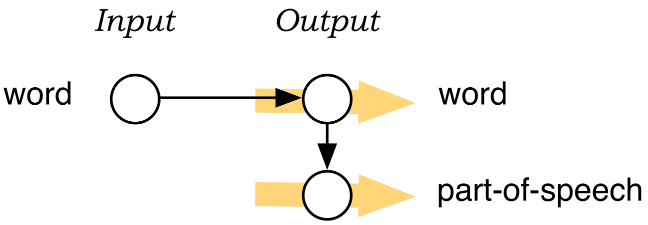


Figure 3.2: Adding part-of-speech information to a statistical machine translation model: By generating POS tags on the target side, it is possible to use high-order language models over these tags that help ensure more grammatical output. In our experiment, we only obtained a minor gain (BLEU 18.25 vs. 18.22).

models trained with the SRILM toolkit). See Table 3.2 for details. On the two different set sets we used, we gained 0.60 and 0.65 BLEU with Model 1 and 0.19 BLEU and 0.48 BLEU with Model 2 for the two test sets, respectively. The additional translation step does not seem to be useful.

3.1.3 Overall grammatical coherence

The previous experiment tried to take advantage of models trained with richer statistics over more general representation of words by focussing the the lexical level. Another aspect of words is their grammatical role in the sentence. A straightforward aspect to focus on are part-of-speech tags. The hope is that constraints on part-of-speech tags might ensure more grammatical output.

The factored translation model that integrates part-of-speech information is very similar to the lemma models from the previous section. See Figure 3.2 for an illustration. Again the additional information on the target side is generated by a generation step, and a language model over this factor is employed.

Since there are only very few part-of-speech tags compared to surface forms of words, it is possible to build very high-order language models for them. In our experiments with used 5-gram and 7-gram models. However, the gains with obtained by adding such a model were only minor: for instance, on the devtest set we imrpoved BLEU to 18.25 from 18.22, while on the test set, no difference in BLEU could be measured.

A closer look at the output of the systems suggests that local grammatical coherence is already fairly good, so that the POS sequence models are not necessary. On the other hand, for large-scale grammatical concerns, the added sequence models are not strong enough to support major restructuring.

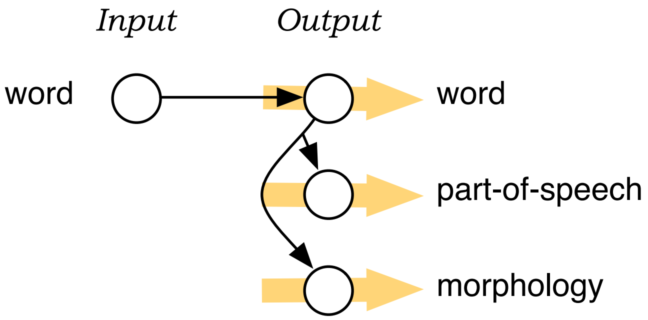


Figure 3.3: Adding morphological information: This enables the incorporation of language models over morphological factors and ensure agreement, especially in local contexts such as noun phrases.

Method	Agreement errors in NP	devtest	test
baseline	15% in NP ≥ 3 words	18.22 BLEU	18.04 BLEU
factored model	4% in NP ≥ 3 words	18.25 BLEU	18.22 BLEU

Table 3.3: Results with the factored translation model integrating morphology from Figure 3.3. Besides minor improvement in BLEU, we drastically reduced the number of agreement errors within noun phrases.

3.1.4 Local agreement (esp. within noun phrases)

The expectation with adding POS tags is to have a handle on relatively local grammatical coherence, i.e. word order, maybe even insertion of the proper function words. Another aspect is morphological coherence. In languages as German not only nouns, but also adjectives and determiners are inflected for count (singular versus plural), case and grammatical gender. When translating from English, there is not sufficient indication from the translation model which inflectional form to chose and the language model is the only means to ensure agreement.

By introducing morphological information as a factor to our model, we expect to be able to detect word sequences with agreement violation. Thus our model should be able to decide that

- *DET-sgl NOUN-sgl* is a good sequence, but
- *DET-sgl NOUN-plural* is a bad sequence

The model for integrating morphological factors is similar to the previous models, see Figure3.3 for an illustration. We generate a morphological tag in addition to the word and part-of-speech tag. This allows us to use a language model over the tags. Tags are generated with the LoPar parser.

When using a 7-gram POS model in addition to the language model, we see minor improvements in BLEU (+0.03 and +0.18 for the devtest and test set, respectively). But an analysis on agreement within noun phrases shows that we dramatically reduced the agreement error rate from 15% to 4%. See Table 3.3 for the summary of the results.

Here two examples, where the factored model outperformed the phrase-based baselines:

- Example 1: rare adjective in-between preposition and noun
  - baseline: *... zur zwischenstaatlichen methoden ...*

  - factored model: *... zu zwischenstaatlichen methoden ...*

- Example 2: too many words between determiner and noun
  - baseline: *... das zweite wichtige änderung ...*
  - factored model: *... die zweite wichtige änderung ...*

In both cases, the language model over surface forms of words is not strong enough. Locally, on a bigram level the word sequences are correct, due to the ambiguity in the morphology of German adjectives. For instance, *zwischenstaatlichen* could be both singular female dative, as the preposition *zur*, or plural, as the noun *methoden*. The agreement error is between preposition and noun, but the language model has to overcome the context of the unusual adjective *zwischenstaatlichen* which is not very frequent in the training corpus. For the morphological tags, however, we have very rich statistics that rule out the erroneous word sequence.

3.1.5 Subject-verb agreement

Besides agreement errors within noun phrases, another source for disfluent German output are agreement errors between subject in verb. In German, subject and verb are often next to each other (for instance, *hans schwimmt.*), but may also be several words apart, which almost always the case in relative clauses (*... damit hans im see ... schwimmt.*).

We could address this problems with factors and skip language models. Consider the following example of a English sentence which may be generated incorrectly by a machine translation system:

the paintings of the old man is beautiful

In this sentence, *old man is* is a better trigram than *old man are* so the language model will more likely prefer the wrong translation. The subject-verb agreement is between the words *paintings* and *are*, which are several words apart. Since this out of the reach of traditional language models, we would want to introduce tags for subject and verb to check for this agreement. For all the other wirdsm, the tag is empty. See the extended example below:

the	**paintings**	**of**	**the**	**old**	**man**	**are**	**beautiful**
-	*SBJ-plural*	-	-	-	-	*V-plural*	-

Given these tags, we should prefer the correct morphological forms:

$$p(\text{-},\textit{SBJ-plural},\text{-},\text{-},\text{-},\text{-},\textit{V-plural},\text{-}) > p(\text{-},\textit{SBJ-plural},\text{-},\text{-},\text{-},\text{-},\textit{V-singular},\text{-})$$

We implemented a skip language model, so that the empty tags are ignored, and the language model decision is simply made on the base of the subject and verb tags:

$$p(\textit{SBJ-plural},\textit{V-plural}) > p(\textit{SBJ-plural},\textit{V-singular})$$

We explored this idea when translating into Spanish, as described in the next section.

3.2 English-Spanish

In this section we describe a series of experiments we conducted using factored models for translation European parliament proceedings from English to Spanish. The motivation for these experiments was to assess the utility of factored translation models for limited resource translation tasks. In the standard phrase-based translation paradigm the translation process

Data Set	**Translation Direction**	**Size**	**Baseline (with different LMs)**
Full Europarl	English → Spanish	950k LM Train 700k Bitext	3-gram LM → 29.35 4-gram LM → 29.57 5-gram LM → 29.54
`EuroMini`	English → Spanish	60k LM Train 40k Bitext	3-gram LM → 23.41 3-gram LM → 25.10 (950k train)

Table 3.4: `EuroMini` and Europarl English-Spanish Corpus Description

is modeled as a $p(\mathbf{e}|\mathbf{f})$ where the target language sentence $\mathbf{e}$ is generated the source sentence $\mathbf{f}$ and both source and target are decomposed into fully inflected substrings or phrases. It is because phrase-based systems directly model the translation strings that they require large amounts of parallel data to train. Intuitively, these data are helpful for modeling both general coocurrence phenomena (such as local agreement) within a language and phrases that translated non-compositionally across languages.

In these experiments, we explore the use of factored models to reduce the data requirements for statistical machine translation. In these models we attempt to improve on the performance of a standard phrase-based model either by explicitly address local agreement or by modeling the translation process through decomposition into different morphological factors. Specifically, we explored models that model lemmatized forms of the parallel training data rather than fully inflected forms. We also experimented with models that attempt to explicitly model agreement through language models of agreement-like features derived from morphological analysis.

To compare the performance of these models we created a small subset of Europarl that we call `EuroMini`. This subset consisted of 40,000 sentence pairs (approximately 5% of the total Europarl Corpus). Table 3.4 shows the statistics for this corpus and BLEU scores from a baseline phrase-based MT system. For these tasks we report results translating from English into Spanish. We choose this task to test whether our factored models could better model the explicit agreement phenomena in Spanish. We compared the results of systems trained on this reduced form of Europarl with:

1. standard models trained on `EuroMini`
2. standard models trained with `EuroMini` with Spanish-side of full Europarl.
3. standard models trained on full Europarl

3.2.1 Sparse Data and Statistical MT for English-Spanish

Like many languages, Spanish exhibits both subject-verb agreement and noun-phrase internal agreement. Spanish verbs must agree with their subjects in both number and person. Spanish noun phrases force determiners, adjectives and nouns to agree in both number and gender. In both cases, the agreement is explicitly marked in Spanish morphology. Examples of these agreement phenomena are shown in Table 3.5.

The inflectional morphology that marks these phenomena in Spanish presents a unique set of problems for statistical language learning in general and MT in specific. First, methods based on counts of surface form words suffer from data fragmentation. Compare, for instance, the English phrase "saw the" (as in "I/he/she/they [saw the] car/bag") with it's possible Spanish translation (shown in Table 3.6).

Each surface shown here differs by only person and number features on the verb "ver" or the gender on the determiner "el." Instead of of learning a relation between underlying lemmatized

Subject Verb Agreement				
Spanish	**Tú**	**quieres**	un	billete
Gloss	you [2p, sing]	want [2p, sing]	a	ticket

Long Distance Subject Verb Agreement										
Spanish	La	**creación**	de	un	grupo	de	alto	nivel	**es**
Gloss	The	creation [3p, sing]	of	a	group	of	high	level/standing	is [3p, sing]

Noun Phrase Agreement			
Spanish	**esta**	**cooperación**	**reforzada**
Gloss	this [sing, f]	cooperation [sing, f]	reinforced/enhanced [sing, f]

Table 3.5: Examples of Spanish Agreement Phenomena

vi al	vi a la	viste al	viste a la
vio al	vio a la	vimos al	vimos a la
vieron al	vieron a la	visteis al	visteis a la

Table 3.6: Examples of Data Fragmentation Due to Poor Generalization

form "ver a el" and the corresponding English phrase, a standard MT system must learn each of the variants shown above. In situations where training data is abundant, this may not cause great difficulty, but when parallel training resources are lacking, the fragmentation shown here could cause poor estimation of translation probabilities. Furthermore, in these situations observation of each phrase variant may not be possible, and a statistical model based on surface forms alone would not be able to produce unseen variants. For statistical MT systems, the lack of ability to generalize could affect all stages of training including word alignment, phrase extraction and language model training.

A second set of problems in Spanish has to do with long distance agreement and is similar to the English example given in Section 3.1.5. In this case, inflectional morphology enforces an agreement relation between two surface forms across a long span. Phrase-based MT systems have difficulty modeling this agreement: typically neither language models or phrase translation models can be reliably estimated for dependencies longer than 3-4 words. This problem is exacerbated in sparse data conditions, and we hypothesize that in these conditions, long term coherence of phrase-based MT output could suffer.

In the sections below we detail two factored translation models that attempt to address these problems specifically. Both models extend the standard surface form model by using morphological analysis and part of speech information. To address the agreement and long-span coherence problems, we construct a model that *generates* agreement features and *checks* these features using a language model trained over morphological features.

We extend this model to address the problems of poor generalization by decomposing the surface-form translation process into two parallel processes: translation of lemmas and morphological features. Lemmas and morphological features are then recombined in a generation process to create target surface forms. Details of both these models and experiments we conducted with them are described below.

For both sets of experiments `EuroMini` data was preprocessed to using FreeLing Atserias et al. [2006] for both part of speech tags and morphological analysis.

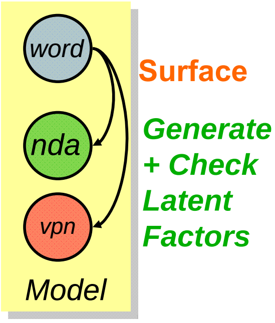


Figure 3.4: Latent Factor Checking using Agreement Features

3.2.2 Explicit Agreement and Coherence Models

In these experiments, we applied factored models as an extension to standard phrase-based MT. In these experiments standard surface-to-surface translation is performed, but we add stochastic constraints on possible target hypotheses to limit enforce (in a soft way) agreement relations. This is done by generating a latent factor (in this case morphological features) from each target word that is hypothesized during decoding. Hypotheses are then scored with both standard MT model components and language models trained over agreement features. Figure 3.4 shows the configuration of two models described below: Verb/Noun/Preposition (VNP) and Noun/Determiner/Adjective (NDA).

This configuration was also used with POS tags to ensure long term coherence. Table 3.7 summarizes different models to explicitly check for agreement and ensure coherence.

Problems Addressed	**Model Type**
Explicit Agreement	– LMs over verbs + subjects – LMs over nouns + determiners + adjectives
Long Span Coherence	– LMs over POS Tags

Table 3.7: LM-based Agreement and Coherence Models

Verb/Subject and Noun-Phrase Agreement Models

In a first set of experiments we used features derived from a morphological analysis of the training data to create n-gram language models.

We produced two models for experimentation. In one, NDA, number and gender features were generated for each noun, determiner and adjective in a hypothesis during decoding. Non-NDA words deterministically generated “don’t care” features.

In a second model, VNP, features required for Spanish verb-subject agreement were chosen in addition the identity of preposition in hypothesized sentences. The inclusion of prepositions allows us potentially to model the selection relationship between verbs and prepositions (though this is not strictly an agreement phenomenon).

Table 3.8 shows the features used for both these models and their possible values.

Since “don’t care” values can intervene between words with NDA and VNP features, we also experimented with language models that skip words lacking features of interest. This

NDA Features
Gender: *masc, fem, common, none*
Number: *sing, plural, invariable, none*
VNP Features
Number: *sing, plural, invariable, none*
Person: *1p, 2p, 3p, none*
Prep-ID: *preposition, none*

Table 3.8: Latent Features used for NDA and VNP models

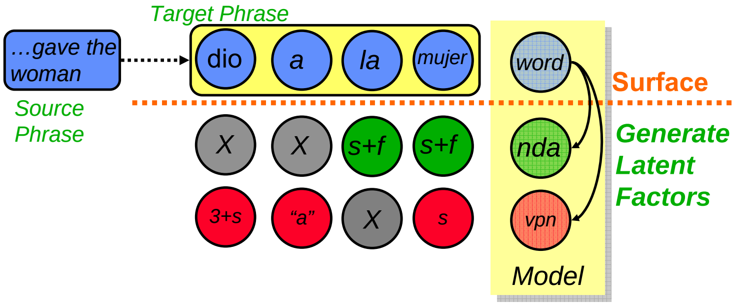


Figure 3.5: Latent Factor Checking using Agreement Features

effectively increases the context length for our n-gram based models and should yield more robust estimation. This is shown schematically in Figure 3.5. Factors marked with "X" are not scored in VNP or NDA language models.

Results with models `EuroMini` corpus using the standard 60k-word 3-gram language model and evaluated against the 2005 ACL Workshop Shared Task are shown in Table 3.9. Both NDA and VPN models improve performance over the baseline system. We ran additional experiments that incorporated all morphological features from our analyzer and this too improved the performance of the system, though inclusion of part of speech information did not. The use of all morphological features closes the gap between the baseline system and it's large LM counterpart by 74%, suggesting that better target language modeling could compensate for the sparsity of target language data.

Model	**BLEU**
Baseline	23.41
Baseline + 950k LM	25.10
NDA	24.47
VPN	24.33
BOTH	**24.54**
NDA w/skipping	24.03
VPN w/skipping	24.16
All Morph Features	**24.66**
All Morph Features + POS Tag	24.25

Table 3.9: Latent Features used for NDA and VNP models

Unfortunately, the use of skipping models didn't improve performance. Further experiments

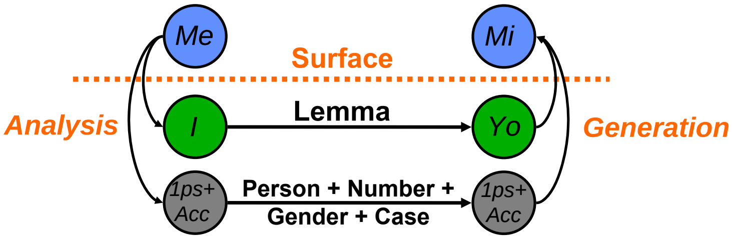


Figure 3.6: A Factored Model for Parallel Translation of Lemmas and Morphology

will be necessary as interactions with pruning during decoding may have limited the performance of these systems.

Lemma-based Models for Translation

The agreement models describe above use a factored approach to add statistical constraints on target language sequences. We attempted to extend this model by improving the underlying translation modeling. To do this, we created a parallel translation model in which source words are decomposed into base lemma and morphological features. Both lemmas and morphological features are translated from the source to the target language. Target words are then recomposed through a statistically trained generation process on the target side. This process is shown schematically in Figure 3.6. Language models are then applied to both morphological features and surface forms to constrain the output.

Table 3.10 shows the performance of this system on a 2005 ACL Workshop Shared Task when a large language model was used (trained with 950k sentences). As these experiments show, the lemma+morphology can lead to improvements through better translation modeling and with the addition of a morphology LM.

Model	**BLEU**
Baseline	25.10
Lemma + Morph	25.93
Lemma + Morph plus Morph LM	26.11

Table 3.10: Results from Lemma+Morphology Models

Scaling Up: POS and Morphology models for Large Data Problems

As long span coherence and agreement remain problems for systems trained on large data, we attempted apply factored models to improve of our large-scale, phrase-based models by using high-order n-gram POS and POS+morphology language models. As Figure 3.7 shows, the performance of these models doesn't seem to improve systems trained on large data.

Although some small gains may be had using POS tags with morphological information in this setting, they are much less pronounced (if at all) than the in the limited `EuroMini` training condition: best-case improvement with large data (1.2% relative, 0.4 BLEU absolute) vs. improvement with `EuroMini` (3.5% relative, 0.84 BLEU absolute). Larger amounts of training data seem to allow the baseline MT system's language and translation models to better learn Spanish agreement constraints. Though not possible during the workshop, in future experiments we hope to examine the effects of scaling parallel translation models to large training as well.

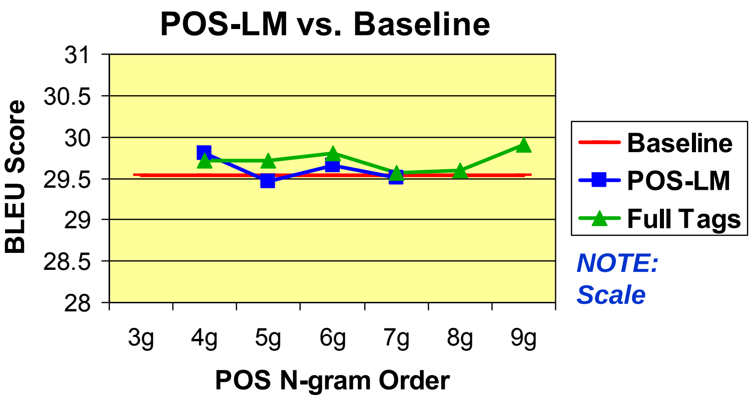


Figure 3.7: Use of Part of Speech Language Models to Improve Long-Span Coherence

3.3 English-Czech

3.3.1 Motivation: Margin for Improving Morphology

Czech is a Slavonic language with very rich morphology and relatively free word order. (See e.g. Bojar [2004] for more details.) The Czech morphological system defines 4,000 tags in theory and 2,000 were actually seen in a big tagged corpus. (For comparison, the English Penn Treebank tagset contains just about 50 tags.) When translating to Czech, any MT system has to face the richness and generate output words in appropriate forms.

Table 3.11 displays BLEU scores of single-factored translation English→Czech using the baseline corpus only. The second line in the table gives the scores if morphological information was disregarded in the evaluation: the MT output is lemmatized (word forms replaced with their respective base forms) and evaluated against lemmatized references.

	Dev (std)	Dev (opt)	Test (opt)
Regular BLEU, lowercase	25.68	29.24	25.23
Lemmatized MT output against lemmatized references	34.29	38.01	33.63

Table 3.11: Margin in BLEU for improving morphology.

We see that more than 8 point BLEU absolute could be achieved if output word forms were chosen correctly.[1] This observation gives us a strong motivation for focussing on morphological errors first.

3.3.2 Scenarios Used

We experimented with the following factored translation scenarios:

The baseline scenario is single-factored: input (English) lowercase word forms are directly translated to target (Czech) lowercase forms. A 3-gram language model (or more models based on various corpora) checks the stream of output word forms.

We call this the "T" (translation) scenario.

[1] Although not all required word forms may be available in the training data, we could easily generate output word forms from lemmas and morphological tags deterministically using a large target-side-only dictionary.

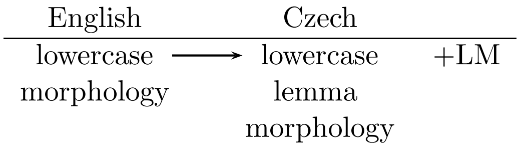


Figure 3.8: Single-factored scenario (T).

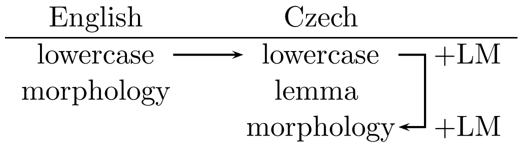


Figure 3.9: Checking morphology (T+C).

In order to check the output not only for word-level coherence but also for morphological coherence, we add a single generation step: input word forms are first translated to output word forms and each output word form then generates its morphological tag.

Two types of language models can be used simultaneously: a (3-gram) LM over word forms and a LM over morphological tags. For the morphological tags, a higher-order LM can be used, such as 7 or 9-gram.

We used tags with various levels of detail, see section B.3.4. We call this the "T+C" (translate and check) scenario.

As a refinement of T+C, we also used T+T+C scenario, where the morphological output stream is constructed based on both, output word forms and input morphology. This setting should ensure correct translation of morphological features such as number of source noun phrases.

Again, two types of language models can be used in this "T+T+C" scenario.

The most complex scenario we used is linguistically appealing: output lemmas (base forms) and morphological tags are generated from input in two independent translation steps and combined in a single generation step to produce output word forms. The input English text was not lemmatized so we used English word forms as the source for producing Czech lemmas.

The "T+T+G" setting allows us to use up to three types of language models. Trigram models are used for word forms and lemmas and 7 or 9-gram language models are used over tags.

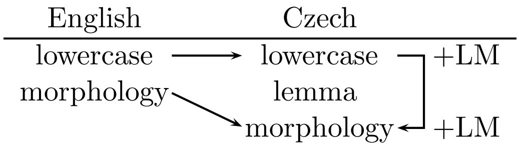


Figure 3.10: Translating and checking morphology (T+T+C).

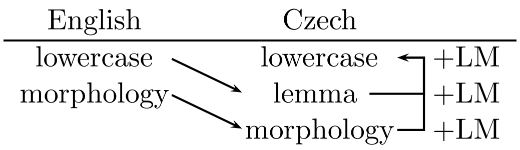


Figure 3.11: Generating forms from lemmas and tags (T+T+G).

3.3.3 Results: Checking Czech morphology works

Table 3.12 summarizes estimated translation quality of the various scenarios. In all experiments, only the baseline corpus of 20k sentences was used with word alignment obtained using grow-diag-final heuristic on stemmed English and lemmatized Czech input streams. Language models are also based on the 20k sentences only, 3-grams are used for word forms and lemmas, 7-grams for morphological tags.

	Dev	Test
Baseline: T	29.24	25.23
T+T+G	30.34	25.94
T+T+C	30.73	26.43
T+C	**30.88**	**27.23**

Table 3.12: BLEU scores of various translation scenarios.

The good news is that multi-factored models always outperform the baseline T. Unfortunately, the more complex a multi-factored scenario is, the worse the results are. Our belief is that this effect is caused by search errors: with multi-factored models, more hypotheses get similar scores and future costs of partial hypotheses might be estimated less reliably. With the limited stack size (not more than 200 hypotheses of the same number of covered input words), the decoder may more often find sub-optimal solutions. The scenario for just checking output morphology (T+C) gives us the best results, 27.23 BLEU, 2 points absolute improvement over the single-factored baseline.

A significantly more detailed analysis of Czech translation, and a number of different experiments are presented in Appendix B.

Chapter 4

Confusion Network Decoding

Machine translation input currently takes the form of simple sequences of words. However, it is desirable to integrate machine translation technology into larger information processing systems with upstream natural language processing tools (such as named entity recognizers, speech recognizers, morphological analyzers, etc.). These upstream processes tend to generate multiple hypotheses which have varying degrees of confidence and accuracy. Current MT systems are designed to process only one input hypothesis, making them vulnerable to errors in the input.

One focus of our workshop was on speech translation, where the input is generated by a speech recognizer. Our aim was to improve performance of spoken language translation by better integrating the output of speech recognition systems with our machine translation system. Errors in the output of speech recognition systems can lead to compounding errors in the machine translation system, as shown in Figure 4.1, which plots the Bleu scores of translations against a speech recognizer's word error rate (WER) for the corresponding input sentences. Rather than rely on a single transcription as input to our system, we instead will utilize a large set of transcription hypotheses generated by the speech recognition system, and combine the scores of the acoustic model, the language model, and the translation model.

Other approaches have been proposed for improving translation quality through the processing of multiple input hypotheses. For instance, better translation performance have been reported by exploiting N-best lists [Zhang et al., 2004; Quan et al., 2005], word lattices [Matusov et al., 2005; Mathias and Byrne, 2006], and confusion networks [Bertoldi and Federico, 2005]. In the workshop we concentrated on *confusion network* decoding Bertoldi and Federico [2005], which is simple to integrate with the translation model and can be efficiently integrated into the search algorithm.

While the focus of this chapter is on the application of confusion networks to the problem of speech translation, the reader should note that their application to machine translation is potentially much broader. Specifically, their inclusion in the decoder may provide a mechanism for dealing with different potential analyses of the input to the machine translation system. This is crucially important when using other natural language processing tools to mark up input sentences for factored translation models.

4.1 Spoken language translation

Translation from speech input is considered more difficult than translation from text for several reasons. Spoken language has many styles and genres, such as, formal read speech, unplanned speeches, interviews, spontaneous conversations; it produces less controlled language, presenting more relaxed syntax and spontaneous speech phenomena.

From a statistical perspective, SLT can be approached as follows. Given the vector $\o$ representing the acoustic observations of the input utterance, let $\mathcal{F}(\o)$ be a set of transcription

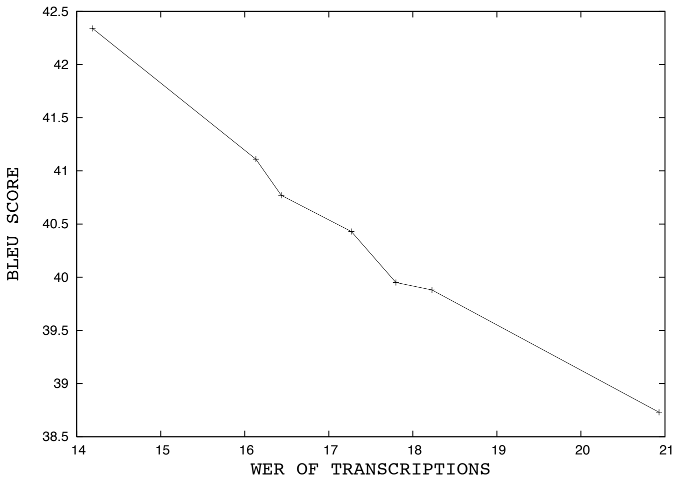


Figure 4.1: Relationship between BLEU score of translations and word error rate of input sentences. Source sentences are transcriptions of parliamentary speeches produced by a speech recognition system.

hypotheses computed by a speech recognizers and represented as a word-graph. The best translation $\mathbf{e}^*$ is searched among all strings in the target language $\mathcal{E}$ through the following criterion:

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \sum_{\mathbf{f} \in \mathcal{F}(\o)} \Pr(\mathbf{e}, \mathbf{f} \mid \o) \tag{4.1}$$

where the source language sentence $\mathbf{f}$ is an hidden variable representing any speech transcription hypothesis. According to the well established log-linear framework, the conditional distribution $\Pr(\mathbf{e}, \mathbf{f} \mid \o)$ can be determined through suitable real-valued feature functions $h_r(\mathbf{e}, \mathbf{f}, \o)$ and real-valued parameters λ_r, $r = 1 \dots R$, and takes the parametric form:

$$p_{\boldsymbol{\lambda}}(\mathbf{e}, \mathbf{f} \mid \o) = \frac{1}{\mathcal{Z}(\o)} \exp \left\{ \sum_{r=1}^{R} \lambda_r h_r(\mathbf{e}, \mathbf{f}, \o) \right\} \tag{4.2}$$

where $\mathcal{Z}(\o)$ is a normalization term.

The main advantage of the log-linear model defined in (4.2) is the possibility of using any kind of features, regarded as important for the sake of translation. The kind of representation used for the set of hypotheses $\mathcal{F}(\o)$ clearly impacts on the implementation of the search algorithm. Here, we assume to have all hypotheses represented as a confusion network.

4.2 Confusion Networks

A Confusion Network (CN) $\mathcal{G}$ is a weighted directed graph with a start node, an end node, and word labels over its edges. The CN has the peculiarity that each path from the start node to the end node goes through all the other nodes. As shown in Figure 4.2, a CN can be represented as a matrix of words whose columns have different depths. Each word $w_{j,k}$ in $\mathcal{G}$ is identified by its column j and its position k in the column; word $w_{j,k}$ is associated to the weight $p_{j,k}$ corresponding to the posterior probability $\Pr(f = w_{j,k} \mid \o, j)$ of having $f = w_{j,k}$ at position j

se$_{.97}$	presenta$_{.40}$	$\epsilon_{.78}$	esas$_{.86}$	elecciones$_{.97}$
he$_{.03}$	presentó$_{.22}$	a$_{.08}$	$\epsilon_{.10}$	selecciones$_{.03}$
	presentan$_{.06}$	e$_{.07}$	esa$_{.04}$	
	...	en$_{.06}$		
		...		

Figure 4.2: Example of confusion network.

given ø. A realization $\mathbf{f} = f_1, \ldots, f_m$ of $\mathcal{G}$ is associated with the probability $\Pr(\mathbf{f} \mid ø)$, which is defined as follows:

$$\Pr(\mathbf{f} \mid ø) = \prod_{j=1}^{m} \Pr(f_j \mid ø, j) \tag{4.3}$$

The generation of a CN from an ASR word-graph [Mangu et al., 2000] can also produce special empty-words ϵ in some columns. These empty-words permit the generation of source sentences of different length and are treated differently from regular words only at the level of feature functions.

4.2.1 Generative translation process

The following process describes how to incrementally generate a translation from a confusion network $\mathcal{G}$:

```
While there are uncovered source columns
Cover a span of columns
Choose a path inside the span
Append a translation of the path to the target
```

4.2.2 CN-based log-linear model

The log-linear model adopted for the CN decoder includes the following feature functions:

1. A word-based n-gram target LM.

2. A reordering model defined in terms of the distance between the first column covered by current span and the last column of the previous span. (In the current implementation, we did not distinguish between regular and empty words.)

3. Four phrase-based lexicon models exploiting statistics at word- and phrase-level. These models remove any empty-word in the source side.

4. Phrase and word penalty models, i.e. counts of the number of phrases and words in the target string.

5. The CN posterior probability, see formula (4.3).

Notice that the above features can grouped into two categories: those which are expansion-dependent because their computation requires some knowledge about the previous step (1, 2), and those which are not (3, 4, 5).

4.2.3 Decoding algorithm

According to the *dynamic programming* paradigm, the optimal solution can be computed through expansions and recombinations of previously computed partial theories. With respect to translating a single input hypothesis, translating from a CN requires, in principle, exploring all possible input paths inside the graph. A key insight is that, due to their linear structure, CN decoding is very similar to text decoding. During the decoding, we have to look up the translation options of spans, i.e. some contiguous sequence of source positions. The main difference between CN and text decoding is that in text decoding there is exactly one source phrase per span, whereas in confusion network decoding there can be multiple source phrases per span. In fact, in a CN the number of source phrases per span is exponential in the span length, assuming its minimum depth is larger than one.

The decoding algorithm can be made much more efficient by pre-fetching translations for all the spans and by applying early recombination.

4.2.4 Early recombination

At each expansion step a span covering a given number of consecutive columns is generated. Due to the presence of empty-words, different paths within the span can generate the same source phrase, hence the same translations. The scores of such paths only impacts the CN posterior feature (5). Additionally, it might happen that two different source phrases of the same span have a common translation. In this case, not only the CN posterior feature is different, but also the phrase translation features (3). This suggests that efficiency can be gained by pre-computing all possible alternative translations for all possible spans, together with their expansion-independent scores, and to recombine these translations in advance.

4.2.5 Pre-fetching of translation options

Concerning the pre-fetching of translations from the phrase-table, an efficient implementation can be achieved if we use a prefix tree representation for the source phrases in the phrase table and generate the translation options incrementally over the span length. So, when looking up a span (j_1, j_2), we can exploit our knowledge about the span $(j_1, j_2 - 1)$. Thus, we have to check only for the known prefixes of $(j_1, j_2 - 1)$ if there exists a successor prefix with a word in column j_2 of the CN. If all the word sequences in the CN also occur in the phrase table, this approach still enumerates an exponential number of phrases. So, the worst case complexity is still exponential in the span length. Nevertheless, this is unlikely to happen in practice. In our experiments, we do not observe the exponential behavior. What we observe is a constant overhead compared to text input.

4.3 N-best decoder

A widely used approach in spoken language translation is the N-best translation, which we used as a baseline for comparison in our experiments.

An alternative way to define the set $\mathcal{F}(\o)$ is to take the N most probable hypotheses computed by the ASR system, i.e. $\mathcal{F}(\o) = \{\mathbf{f}_1, \dots, \mathbf{f}_N\}$. By taking a maximum approximation over $\mathcal{F}(\o)$, and assuming that $\Pr(\tilde{\mathbf{e}}, \mathbf{f} \mid \o) = \Pr(\mathbf{f} \mid \o) \Pr(\tilde{\mathbf{e}} \mid \mathbf{f})$, we get the search criterion:

$$\tilde{\mathbf{e}}^* \approx \arg\max_{n=1,..,N} \Pr(\mathbf{f}_n \mid \o) \max_{\tilde{\mathbf{e}}} \Pr(\tilde{\mathbf{e}} \mid \mathbf{f}_n) \quad (4.4)$$

In the equation above we can isolate N independent translation tasks (rightmost maximization), and the recombination of their results (leftmost maximization). Hence, the search criterion can be restated as:

$$
\begin{aligned}
\tilde{\mathbf{e}}_n^* &= \arg\max_{\tilde{\mathbf{e}}} \Pr(\tilde{\mathbf{e}} \mid \mathbf{f}_n) \qquad n = 1, \ldots, N && (4.5)\\
\tilde{\mathbf{e}}^* &\approx \arg\max_{n=1,..,N} \Pr(\mathbf{f}_n \mid \o) \Pr(\tilde{\mathbf{e}}_n^* \mid \mathbf{f}_n) && (4.6)
\end{aligned}
$$

In other words: the best translation $\tilde{\mathbf{e}}_n^*$ of each transcription hypothesis $\mathbf{f}_n$ is found; then, the best translation $\tilde{\mathbf{e}}^*$ is selected among $\{\tilde{\mathbf{e}}_1^*, \ldots, \tilde{\mathbf{e}}_N^*\}$ according to its score weighted by the ASR posterior probability $\Pr(\mathbf{f}_n \mid \o)$.

In the experimental chapters we will compare performance of the CN decoder against the above N-best approach.

Chapter 5

Experiments with Confusion Nets

5.1 Results for the BTEC Task

The experiments were carried out on the *Basic Travel Expression Corpus* (BTEC) task Takezawa et al. [2002]. This is a multilingual speech corpus which contains tourism-related sentences similar to those that are found in phrase books. The corpus statistics are shown in Table 5.1. For the supplied data track, 40 000 sentences training corpus and three test sets were made available for each language pair.

5.1.1 Chinese-to-English

In this section, we will present the experimental results for the Chinese–English task. The statistics of the confusion networks are summarized in Table 5.2. Note that the average length of the sentences in the `dev4` test set is about twice as large as in the training data. We also present the depths of the confusion networks. On average we have between two and three alternatives per position. At some positions, however, there are more than 90 alternatives.

In Table 5.3, we present the translation results for the Chinese–English task for different input conditions on the `dev4` and the `eval` test sets. Comparing the translation results of 1-best and confusion network, we observe a small but consistent improvement for read speech. For spontaneous speech, the improvements are larger, e.g. 1.1% BLEU for the `eval` test set.

5.2 Results for the EPPS Task

Additional experiments for confusion network decoding were carried out on the Spanish-to-English EPPS (European Parliament Plenary Sessions) task. The training data was collected within the TC-Star project[1] and is a superset of the Spanish–English EuroParl corpus (Koehn [2005]).

[1] http://www.tc-star.org

Table 5.1: Corpus statistics for the Chinese-English task.

	Chinese	English
sentences	40 K	
running words	351 K	365 K
avg. sent. length	8.8	9.1
vocabulary entries	11 K	10 K

Table 5.2: Chinese–English: confusion network statistics for the `dev4` test set (489 sentences).

	speech type	
	read	spontaneous
avg. length	17.2	17.4
avg. / max. depth	2.2 / 92	2.9 / 82
avg. number of paths	10^{21}	10^{32}

Table 5.3: Chinese–English: translation results for different input types.

		speech type	
test set	input	read BLEU [%]	spontaneous BLEU [%]
`dev4`	verbatim	21.4	
	1-best	19.0	17.2
	full CN	19.3	17.8
`eval`	verbatim	21.4	
	1-best	18.5	17.0
	full CN	18.6	18.1

5.2.1 Corpus Statistics

Statistics for this task are reported in Table 5.4. The bilingual training corpus consists of about 1.3 M sentence pairs with about 36 M running words in each language. The training was performed with the `Moses` training tools, while training of the 4-gram target LM was performed with the IRST LM Toolkit. Sentences in the dev and test sets are provided with two reference translations each.

The ASR word lattices were kindly provided by CNRS-LIMSI, France. The confusion networks and N-best lists were extracted using the `lattice-tool` included in the SRILM Toolkit (Stolcke [2002]). The statistics of the confusion networks for the Spanish–English EPPS task are presented in Table 5.5. The average depth of the confusion networks, i.e. the average number of alternatives per position, is 2.8 for the development set and 2.7 for the test set. Note that the maximum depth is much larger, e.g. up to 165 for the development set. Also, the average number of paths in the confusion networks is huge.

5.2.2 Parameter Tuning

The feature weights of all models were optimized using minimum-error-rate training (Och [2003]) which tries to maximize the BLEU score on the development set. A special procedure was used for tuning the weights of the N-best translation system. First, a single best decoder was optimized over the development set. Then M-best translations were generated for each N-best input of the development set. Hence, all NxM translations were merged and a new log-linear model including the ASR additional features was trained.

5.2.3 Translation Results

In Table 5.6, we report the translation performance for different input types:

- `verbatim`: These are the translation results for the correct transcriptions of the speech signal. Therefore, the ASR word error rate is 0.0% for this input type.

Table 5.4: Corpus statistics for the Spanish-English EPPS task.

		Spanish	English
Train	Sentences	1.3 M	
	Words	37 M	36 M
	Vocabulary	143 K	110 K
	Phrase Pairs	83 M	
	Phrases	48 M	44 M
Dev	Utterances	2 643	
	Words	20 384	20 579
Test	Utterances	1 073	
	Words	18 890	18 758

Table 5.5: Statistics of the confusion networks for the development and test sets of the Spanish–English EPPS task.

	Dev	Test
Utterances	2 633	1 071
Avg. length	10.6	23.6
Avg. / max. depth	2.8 / 165	2.7 / 136
Avg. number of paths	10^{38}	10^{75}

- `1-best`: Here, we have translated the single-best ASR transcription of the word graphs (`wg`) and the confusion networks (`cn`), respectively.
- `cn`: These are the results for decoding the full confusion networks.
- `N-best`: These are the results for N-best decoding with $N = 1, 5, 10$.

The optimization of the system was performed separately for each input type, as described before. In addition to the translation results, we also report the ASR word error rate. Note that for the confusion network (`cn`) and the N-best lists (`N-best`) input types, we reported the ASR WER of the best transcription contained in the confusion network or the N-best lists, respectively. The comparison of the scores for the different input conditions shows a strong correlation between quality of the transcriptions given by the ASR WER and quality of the translation given by the MT scores.

Assuming a perfect ASR system, i.e. in the `verbatim` condition, we achieve a BLEU score of 48%. Comparing this to the ASR input conditions, we observe a degradation of about 10 BLEU points in the case of ASR input.

The confusion network decoding (`cn`) achieves the best BLEU score among the ASR input types. Note the large gain compared to the single-best input types, e.g. 1.6% BLEU absolute over the single-best from the word graphs and even more over the single-best from the confusion networks.

In terms of WER and PER, the `5-best` system is slightly better. This could be due to the fact that the systems were optimized for BLEU.

5.2.4 Efficiency

Experimentally, the ratio between the decoding time for translating the confusion networks (`cn`) and the single-best (`1-best`) is about 2.1 (87.5 vs 42.5 seconds per sentence). As the decoding

Table 5.6: Translation performance achieved by `Moses` for different input types for the test set of the Spanish–English EPPS task.

Input Type		ASR WER [%]	BLEU [%]	PER [%]	WER [%]
`verbatim`		0.00	48.00	31.19	40.96
ASR	`1-best, wg`	22.41	37.57	39.24	50.01
	`cn`	23.30	36.98	39.17	49.98
	`cn`	8.45	39.17	38.64	49.52
	`N-best, N=1`	22.41	37.57	39.24	50.01
	`N=5`	18.61	38.68	38.55	49.33
	`N=10`	17.12	38.61	38.69	49.46

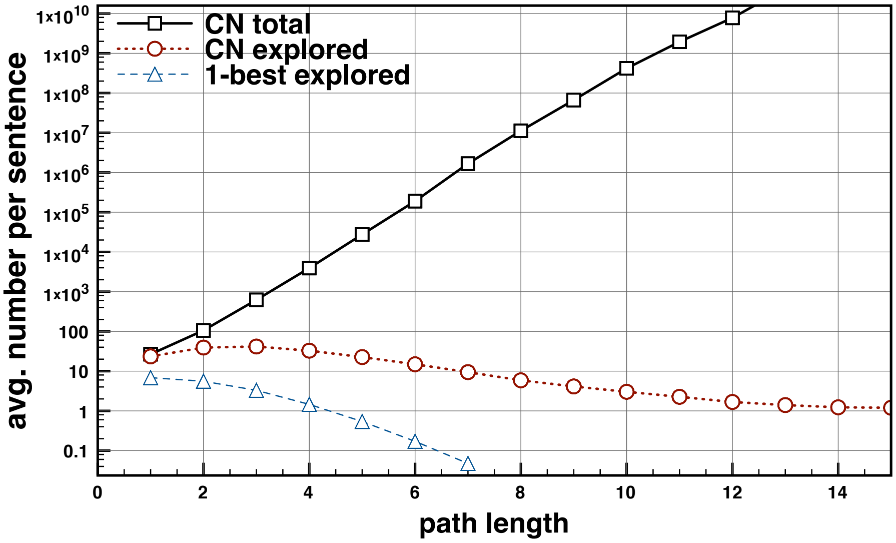


Figure 5.1: Exploration of the confusion networks for the Spanish–English EPPS task.

time for N-best lists is proportional to N, we can claim that decoding CNs is preferrable to translating N-best ($N > 2$) with respect to translation speed, i.e. decoding confusion networks is more efficient than translating N-best lists.

In Figure 5.1, we show the effect of the incremental pre-fetching of translation options for confusion network decoding. The curve labeled 'CN total', represents the total number of paths in the confusion networks as a function of the path length. This is the number of phrases enumerated using a naive pre-fetching algorithm. Note the exponential growth with increasing path length. Therefore, the naive algorithm is only applicable for very short phrases and heavily pruned confusion networks. The next curve, labeled 'CN explored', is the number of paths that are actually explored using the incremental algorithm described in Section 4.2.5. We do *not* observe the exponential explosion as for the total number of paths. For comparison, we also plotted the number of explored paths for the case of single-best input, labeled '1-best explored'. The maximum phrase length in the phrase table for these experiments is seven. In the case of confusion network input, this length can be exceeded as the confusion networks may contain ϵ-transitions.

Chapter 6

Open Source Toolkit

6.1 Overall design

In developing the Moses decoder we were aware that the system should be open-sourced if it were to gain the support and interest from the machine translation community that we had hoped. There were already several proprietary decoders available which frustrated the community as the details of their algorithms could not be analysed or changed. However, making the source freely available is not enough. The decoder must also advance the state-of-the-art in machine translation to be of interest to other researchers. Its translation quality and runtime resource consumption must be comparable with the best available decoders. Also, as far as possible, it should be compatible with current systems which minimize the learning curve for people who wish to migrate to Moses. We therefore kept to the following principles when developing Moses:

- Accessibility
- Easy to Maintain
- Flexibility
- Easy for distributed team development
- Portability

By adding factored translation to conventional phrase based decoding we hope to incorporate linguistic information into the translation process in order to create a competitive system.

Resource consumption is of great importance to researchers as it often determine whether or not experiments can be run or what compromises needs to be taken. We therefore also benchmarked resource usage against another phrase-based decoder, Pharaoh, as well as other decoders, to ensure that they were comparable in like-for-like decoding.

It is essential that features can be easily added, changed or replace, and that the decoder can be used as a toolkit in ways not originally envisaged. We followed strict object oriented methodology; all functionality was abstracted into classes which can be more readily changed and extended. For example, we have two implementations of single factor language models which can be used depending on the functionality and licensing terms required. Other implementations for very large and distributed LMs are in the pipeline and can easily be integrated into Moses. The framework also allows for factored LMs; a joint factor and skipping LM are currently available.

Another example is the extension of Moses to accept confusion networks as input. This also required changes to the decoding mechanism.

Nevertheless, there will be occasions when changes need to be made which are unforeseen and unprepared. In these cases, the coding practices and styles we instigated should help, ensuring

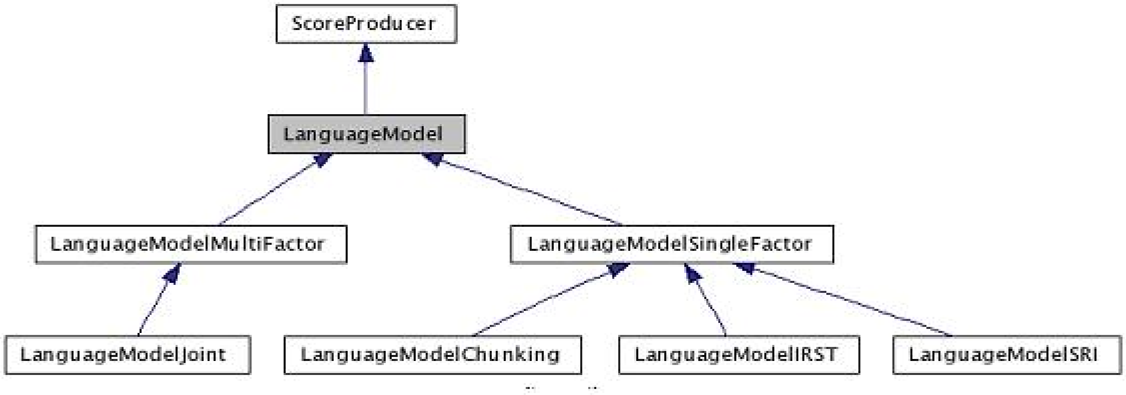


Figure 6.1: Language Model Framework

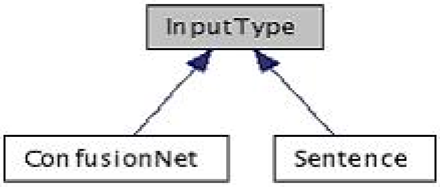


Figure 6.2: Input

that the source code is clear, modular and consistent to enable the developers to quickly assess the algorithms and dependencies of any classes or functions that they may need to change.

A major change was implemented when we decided to collect all the score keeping information and functionality into one place. That this was implemented relatively painlessly must be partly due to the clarity of the source code.

The decoder is packaged as a library to enable users to more easily comply with the LGPL license. The library can also be embedded in other programs, for example a GUI front-end or an integrated speech to text translator.

6.1.1 Entry Point to Moses library

The main entry point to the library is the class

```
Manager
```

For each sentence or confusion network to be decoded, this class is instantiated and the following function called

```
ProcessSentence()
```

Its outline is shown below

```
CreateTranslationOptions()
for each stack in m_hypoStack
   prune stack
   for each hypothesis in stack
      ProcessOneHypothesis()
```

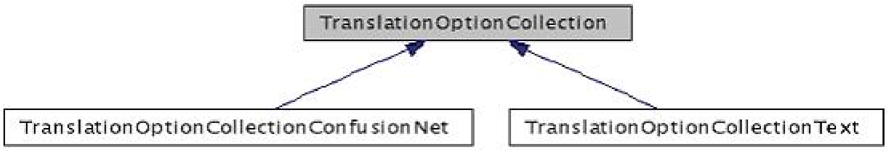

TranslationOptionCollection
TranslationOptionCollectionConfusionNet
TranslationOptionCollectionText

Figure 6.3: Translation Option Collection

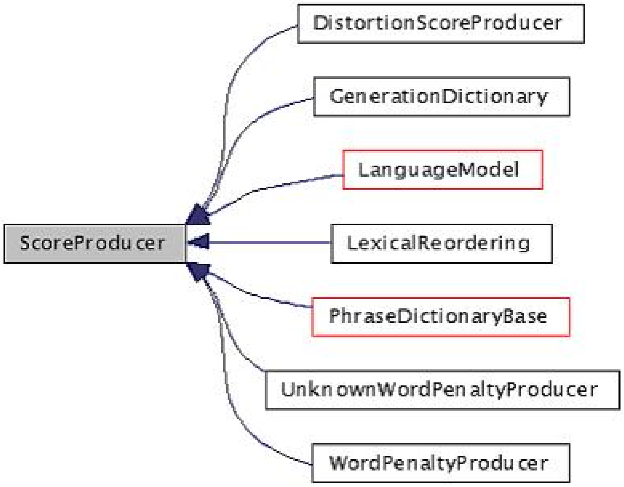


Figure 6.4: Scoring framework

Each contiguous word coverage (”span”) of the source sentence is analysed in

```
CreateTranslationOptions()
```

and translations are created for that span. Then each hypothesis in each stack is processed in a loop. This loop starts with the stack where nothing has been translated which has been initialised with one empty hypothesis.

6.1.2 Creating Translations for Spans

The outline of the function

```
TranslationOptionCollection::CreateTranslationOptions()
```

is as follows:

```
for each span of the source input
   CreateTranslationOptionsForRange(span)
ProcessUnknownWord()
Prune()
CalcFutureScoreMatrix()
```

A translation option is a pre-processed translation of the source span, taking into account all the translation and generation steps required. Translations options are created in

```
CreateTranslationOptionsForRange()
```

which is out follows

```
ProcessInitialTranslation()
```

```
for every subequent decoding step
   if step is Translation
      DecodeStepTranslation::Process()
   else if step is Generation
      DecodeStepGeneration::Process()
Store translation options for use by decoder
```

However, each decoding step, whether translation or generation, is a subclass of

`DecodeStep`

so that the correct Process() is selected by polymorphism rather than using if statements as outlined above.

6.1.3 Unknown Word Processing

After translation options have been created for all contiguous spans, some positions may not have any translation options which covers it. In these cases, CreateTranslationOptionsForRange() is called again but the table limits on phrase and generation tables are ignored.

If this still fails to cover the position, then a new target word is create by copying the string for each factor from the untranslatable source word, or the string "UNK" if the source factor is null.

Source Word		New Target Word
Jimmy	→	Jimmy
Proper Noun	→	Proper Noun
-	→	UNK
-	→	UNK

This algorithm is suitable for proper nouns and numbers, which are one of the main causes of unknown words, but is incorrect for rare conjugation of source words which have not been seen in the training corpus. The algorithm also assumes that the factor set are the same for both source and target language, for instance, th list of POS tags are the same for source and target. This is clearly not the case for the majority of language pairs. Language dependent processing of unknown words, perhaps based on morphology. is a subject of debate for inclusion into Moses.

Unknown word processing is also dependent on the input type - either sentences or confusion networks. This is handled by polymorphism, the call stack is

```
Base::ProcessUnknownWord()
   Inherited::ProcessUnknownWord(position)
      Base::ProcessOneUnknownWord()
```

where

`Inherited::ProcessUnknownWord(position)`

is dependent on the input type.

6.1.4 Scoring

A class is created which inherits from

`ScoreProducer`

for each scoring model. Moses currently uses the following scoring models:

Scoringmodel	*Class*
Distortion	DistortionScoreProducer
WordPenalty	WordPenaltyProducer
Translation	PhraseDictionary
Generation	GenerationDictionary
LanguageModel	LanguageModel

The scoring framework includes the classes
`ScoreIndexManager`
`ScoreComponentCollection`
which takes care of maintaining and combining the scores from the different models for each hypothesis.

6.1.5 Hypothesis

A hypothesis represents a complete or incomplete translation of the source. Its main properties are

Variables	
m_sourceCompleted	Which source words have already been translated
m_currSourceWordsRange	Source span current being translated
m_targetPhrase	Target phrase currently being used
m_prevHypo	Pointer to preceding hypothesis that translated the other words, not including m_currSourceWordsRange
m_scoreBreakdown	Scores of each scoring model
m_arcList	List of equivalent hypothesis which have lower score than current hypothesis

Hypothesis are created by calling the constructor with the preceding hypothesis and an appropriate translation option. The constructors have been wrapped with static functions, Create(), to make use of a memory pool of hypotheses for performance.

Many of the functionality in the Hypothesis class are for scoring. The outline call stack for this is

```
CalcScore()
   CalcDistortionScore()
   CalcLMScore()
   CalcFutureScore()
```

The Hypothesis class also contains functions for recombination with other hypotheses. Before a hypothesis is added to a decoding stack, it is compare to other other hypotheses on the stack. If they have translated the same source words and the last n-words for each target factor are the same (where n is determined by the language models on that factor), then only the best scoring hypothesis will be kept. The losing hypothesis may be used latter when generating the n-best list but it is otherwise not used for creating the best translation.

In practise, language models often backoff to lower n-gram than the context words they are given. Where it is available, we use information on the backoff to more agressively recombine hypotheses, potentially speeding up the decoding.

The hypothesis comparison is evaluated in
`NGramCompare()`
while the recombination is processed in the hypothesis stack class
`HypothesisCollection::AddPrune()`

and in the comparison functor class
`HypothesisRecombinationOrderer`

6.1.6 Phrase Tables

The main function of the phrase table is to look up target phrases give a source phrase, encapsulated in the function
`PhraseDictionary::GetTargetPhraseCollection()`
There are currently two implementation of the PhraseDictionary class

PhraseDictionaryMemory	Based on std::map. Phrase table loaded completely and held in memory
PhraseDictionaryTreeAdaptor	Binarized phrase table held on disk and loaded on demand.

6.1.7 Command Line Interface

The subproject, moses-cmd, is a user of the Moses library and provides an illustration on how the library functions should be called.

However, since most researchers will be using a command line program for running experiments, it will remain the defacto Moses application for the time being.

Apart from the main() function, there are two classes which inherites from the moses abstract class, InputOutput:

```
IOCommandLine
IOFile (inherites from IOCommandLine)
```

These implement the required functions to read and write input and output (sentences and confusion network inputs, target phrases and n-best lists) from standard io or files.

6.2 Software Engineering Aspects

6.2.1 Regression Tests

Moses includes a suite of regression tests designed to ensure that behavior that has been previously determined to be correct does not break when new functionality is added, when bugs are fixed, or when performance improvements are made. The baseline behavior for the regression testing is determined in three ways:

1. Expected behavior based on off-line calculations (for example, given a small phrase table and sample input, one can work through the search space manually and compute the expected scores for a translation hypothesis).

2. Expected values based on comparisons with other systems (for example, language modeling toolkits provide the ability to score a sentence. Such a tool can be used to calculate the expected value of the language model score that will be produced by the decoder).

3. Expected values based on previous behavior of the decoder (some output behavior is so complex that it is impractical or impossible to determine externally what the expected values are; however, it is reasonable to assume that localized bug-fixes, the addition of new functionality, or performance improvements should not impact existing behavior).

The nature of statistical machine translation decoding makes achieving substantial and adequate test coverage possible with simple black-box testing. Aggregate statistics on the number of hypotheses generated, pruned, explored, as well as comparisons of the exact costs and translations for certain sample sentences provide ample evidence that the models and code that is utilized in decoding is working adequately since these values tend to be highly sensitive to even minor changes in behavior.

How it works

The test harness (invoked with the command `run-test-suite`) runs the decoder that is to be tested (specified to the script with the `--decoder` command line option) with a series of configuration files and translation inputs. The output from the decoder, which is written to `stdout` and `stderr`, is post-processed by small scripts that pull out the data that is going to be compared for testing purposes. These values are compared with the baseline and a summary is generated.

Timing information is also provided so that changes that have serious performance implications can be identified as they are made. This information is dependent on a variety of factors (system load, disk speed), so it is only useful as a rough estimate.

Versioning

The code for the regression test suite is in the `regression/tests` subdirectory of the Subversion repository. The inputs and expected values for each test case in the test suite are stored together in `regression-tests/tests`. The test suite is versioned together with the source code for several reasons:

1. As bugs are identified and fixed that change existing behavior, the testing code needs to be updated.

2. As new functionality is added, testing code exercising this functionality needs to be added.

By versioning the regression tests together with the source code, it should be possible to minimize when developers need to worry about expected test failures.

The data (language models, phrase tables, generation tables, etc.) that is used by the individual test cases is versioned along with the source code, but because of its size (currently about 60MB), it is not stored in Subversion. When test suite is run in a new environment or one with an improper version of the test data, it will fail and provide instructions for retrieving and installing the proper version of the testing data (via HTTP) from the test data repository, which is currently `http://statmt.org`.

Making changes to existing tests

As changes are made that effect the decoder's interface (output format, command line interface, or configuration file format) and bugs that effect existing decoder behavior are fixed, it will often be necessary to update either the expected values, the scripts that post-process the decoder output, or the configuration files. These files can be edited in the same manner as the rest of the source code and should be submitted along with the corresponding code changes.

If changes need to be made to the test data, a new tar-ball must be generated that contains all of the test data for all regression tests and submitted to the repository maintainer. Once it is available for download, the `TEST_DATA_VERSION` constant in `MosesRegressionTesting.pm` can be incremented to point to the new version.

Adding regression tests

As new functionality is incorporated into Moses, regression tests should be added that guarantee that it will continue to be behave properly as further changes are made. Generally, testing

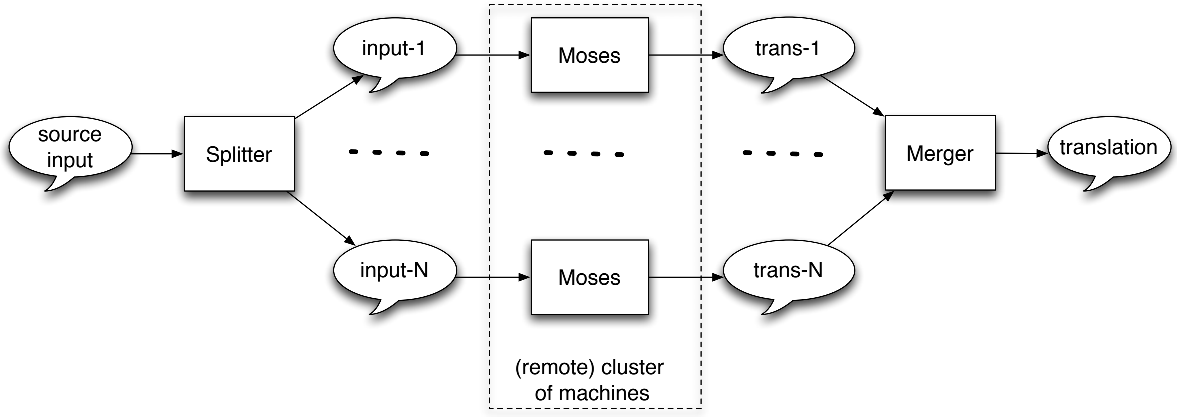


Figure 6.5: The parallelization module for `Moses`.

new models with multi-factored models is recommended since common single-factored models exercise only a subset of the logic.

If new regression tests have new data dependencies, the test data will need to be updated. For more information on this workflow, refer to the previous section.

6.3 Parallelization

The decoder implemented in `Moses` translates its input sequentially; in order to increase the speed of the toolkit a parallelization module was developed which exploits several instances of the decoder and feed them with subsets of the scource input.

As shown in Figure 6.5, the procedure we implemented is reasonably easy: first, the source input is equally divided into N parts, then N instances of the `Moses` translate them; finally, the full translation is obtained by ordering and merging the translation of all input parts.

All `Moses` instances are assumed to run on a (possibly remote) cluster. No restriction on the number of `Moses` instances is given.

Time to perform a full translation with one `Moses` instance comprises the time to load data, which is constant, and time to translate the input, which is proportional to its size. The parallelization module requires an additional time to access the cluster, which is strictly related to the real load of the cluster itself and hardly forecastable. Time to split the input and merge the output can be considered negligible with respect to the translation time. Moreover, an "ending" delay can be observed because the merging module should wait that all decoders have completed their translations, and this does not necessarily happen at the same time. A good splitting policy which allows a balanced translation time among all decoders, improves the effciency of the whole parallelization module.

We tested the gain in time that the parallelization module can provide to the toolkit on the Spanish-English EuroParl task. 3 input sets were created of 10, 100 1000 sentences and translated using a standalone `Moses`, and the parallelization module exploiting difference number of `Moses` instances (1, 5, 10, 20). Decoders ran on the 18-processor CLSP cluster. As in the real situation, its load was not in control, and hence the immediate availability of the processors was not assured. Table 6.3 reports the average translation times for all conditions.

Some considerations can be drawn by inspecting these figures.

- Parallelization is not effective if source input is small, because time to access the cluster dominates overall runtime.

	standalone	1 proc	5 proc	10 proc	20 proc
10 sentences	6.3	13.1	9.0	9.0	–
100 sentences	5.2	5.6	3.0	1.7	1.7
1000 sentences	6.3	6.5	2.0	1.6	1.1

Table 6.1: Average time (seconds) to translate 3 input sets with a standalone `Moses` and with its parallel version.

- Trivially, there is no reason to use the parallelization module if just one processor is required.
- Parallelization is beneficial if more instances of `Moses` are exploited.
- The gain in time is not exactly proportional to the number of decoder instances, mainly due to the effect of "ending" delay, where results are aggregated .

In conclusion, the choice of the number of splits N is essential for a good efficiency of the parallelization module, and depends on the available computational power, the cluster load, and the average translation time of the standalone decoder.

6.4 Tuning

As described in Section 4.1, `Moses` decoder relies on a log-linear model to search for the best translation $\mathbf{e}^*$ given an input string $\mathbf{f}$:

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \Pr(\mathbf{e} \mid \mathbf{f}) = \arg\max_{\mathbf{e}} p_\lambda(\mathbf{e} \mid \mathbf{f}) = \arg\max_{\mathbf{e}} \sum_i \lambda_i h_i(\mathbf{e}, \mathbf{f}) \tag{6.1}$$

Main components of a log-linear model are the real-valued feature functions h_i and their real-valued weights λ_i. To get the best performance from this model all components need to be estimated and optimized for the specific task the model is applied to.

Feature functions model specific aspects of the translation process, like the fluency, the adequacy, the reordering. Features can correspond to any function of $\mathbf{e}$ and $\mathbf{f}$, and there is no restriction about the values they assume. Some features are based on statistical models which are estimated on specific training data.

Feature weights are useful to balance the (possibly very different) ranges of the feature functions, and to weigh their relative contribution. The most common way to estimate the weights of a log-linear model is called Minimum Error Rate Training (MERT). It consists in an automatic procedure which search for the weights minimizing translation errors on a development set.

In this section we assume that the input type is text string, but trivially there is no matter if input is a Confusion Network, because MERT just estimates weights of the log-linear combination regardless the type and the number of features.

Let $\mathbf{f}$ be a source sentence and $\mathbf{ref}$ the set of its reference translations; let $\mathbf{Err}(\mathbf{e}; \mathbf{ref})$ be an error function which measures the quality of a given translation $\mathbf{e}$ with respect to the references $\mathbf{ref}$. The MERT paradigm can be formally stated as follows:

$$\mathbf{e}^* = \mathbf{e}^*(\lambda) = \arg\max_{\mathbf{e}} p_\lambda(\mathbf{e} \mid \mathbf{f}) \tag{6.2}$$

$$\lambda^* = \arg\min_{\lambda} \mathbf{Err}(\mathbf{e}^*(\lambda); \mathbf{ref}) \tag{6.3}$$

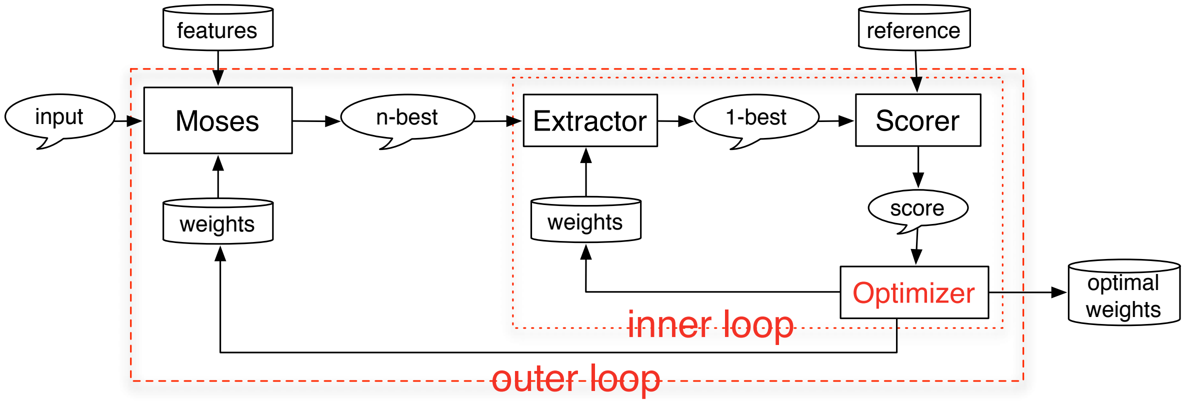


Figure 6.6: An high-level picture of the Minimum Error Rate Training module for the optimization of the feature weights.

where $\mathbf{e}^*(\lambda)$ is the best translation found by the decoder exploiting a given set of weights λ.

The error function needs to be computed automatically from **e** and **ref** without human intervention. Word Error Rate (WER), Position Independent Word Error Rate (PER), (100-BLEU score), NIST score, or any combination of them are good candidates as automatic scoring functions.

An error function is rarely mathematically sound, and hence an exact solution of the previous problem is not usually known. Hence, algorithms like the gradient descent or the downhill simplex, are exploited which iteratively approximate the optimal solution. Unfortunately, these approximate algorithms frequently get stuck in a local optimum.

The MERT procedure we implemented during the workshop is depicted in Figure 6.6. It is based on two nested loops, which are now described.

In the outer loop

1. initial weights λ^0, an empty list of translation hypotheses T^0, and the iteration index $t = 0$ are set;
2. `Moses` translates the input with λ^t and generates a list of N-best translation hypotheses T^t;
3. T^t are added to the previous lists $T^0, \ldots T^{t-1}$;
4. the inner loop is performed (see below) on the new list $\bigcup_{i=0}^{t} T^i$ and with the weights λ^t;
5. the new set of weights λ^{t+1} provided by the inner loop are set;
6. t is increased by 1, and the loop restarts from 2.

The outer loop ends when the list of translation hypotheses does not increase anymore.

In the inner loop which is fed with a list of hypotheses and a set of weights $\bar{\lambda}$

1. initial weights λ^0 are set to $\bar{\lambda}$, and the iteration index $s = 0$ is set;
2. all translation hypotheses in the list are rescored according with the actual weights λ^s and the best-scored hypothesis is extracted (`Extractor`);
3. the error measure of such translation is computed (`Scorer`);

4. the `Optimizer` suggests a new set of weights λ^{s+1};

5. s is increased by 1, and the loop restarts from 2.

The inner loop ends when the error measure does not improve anymore. As the `Optimizer` provides a local optimum for the weights, and strongly depends on the starting point $\bar{\lambda}$, the inner loop starts over several times with different choices of $\bar{\lambda}$. The first time the weights λ^t used by `Moses` in the last outer loop are applied; the next times random sets are exploited. The best set of weights are then provided to the outer loop again.

Instead of standard approximate algorithms like the gradient descent or the downhill simplex, in the workshop we employed an `Optimizer` based on the idea proposed by Och [2003] and developed by David Chiang (USC-ISI). The algorithm strongly relies on the availability of a finite list of translation alternatives, because this allows a discretization of the r-dimensional space of the weights (r is the number of weights). This makes the search of the optimum faster. The algorithm iteratively optimizes one weight at a time.

The `Scorer` employed in the workshop computes BLEU score.

The time spent for each iteration of the outer is basically proportional to the size of the input because the translation of the whole input is required. The time for each iteration of the inner loop is proportional to the amount of translation hypotheses because all of them have to be re-scored and evaluated,

6.4.1 Tuning Experiments

We analized how much the experimental set up affects the effectiveness of MERT. In particular, the amount of translation hypotheses extracted in each outer loop and the size of the development set are taken into account.

Experiments were carried out on two tasks, namely the translation of proceedings of the European Parliament from German into English, and the translation of speeches from the European Parliament Plenary Sessions (EPPS) from Spanish to English.

The German-English EuroParl task EuroParl Koehn [2005] is a collection of parallel text in 11 languages from the proceedings of the European Parliament. We worked on the German-English language pair. Training data consist of 751 K sentence pairs. 2000 sentences are provided both for parameter tuning and for testing. Statistics about training data, development and test sets are reported in Table 6.2 Sentences in the development and test sets are provided with just 1 reference translation each.

	Train		Dev		Test	
	Ger	Eng	Ger	Eng	Ger	Eng
Sentences	751 K		2,000		2,000	
Words	15 M	16 M	55,136	58,652	54,247	57,945
Vocabulary	195 K	66 K	8,796	6,114	8,668	6,054
Phrase Pairs	12 M					
Phrases	9 M	8 M				

Table 6.2: Statistics of the German-English EuroParl task. Word counts of English dev and test sets refer the first reference translation.

Models employed in the decoder were estimated with the `Moses` toolkit. A 3-gram target language model was used.

The EPPS task The EPPS task consists in translating speeches from the European Parliament from Spanish to English, This task was organized in the TC-STAR 2005[1] Evaluation Campaign.

Speeches included in the development and test sets are automatically recognized by LIMSI, France, which kindly provided the word lattices, and Confusion Networks were extracted from them using the `lattice-tool` software of the `SRILM Toolkit` Stolcke [2002]. Instead, training data for the EPPS task consists of the Final Text Editions of the speeches, which are significantly human-revised versions of the simultaneous transcriptions. Statistics about the training, development and testing data are reported in Table 6.3. Sentences in the development and test sets are provided with two reference translations each.

	Train		Dev		Test	
	Spa	Eng	Spa	Eng	Spa	Eng
Sentences	1,308 K		2,643		1,073	
Words	37 M	36 M	20,384	20,579	18,890	18,758
Vocabulary	143 K	110 K	2,883	2,362	3,139	2,567
Phrase Pairs	83 M					
Phrases	48 M	44 M				

Table 6.3: Statistics of the EPPS speech translation task. Word counts of dev and test sets sets refer to human transcriptions (Spanish) and the first reference translation (English).

Models were estimated with the `Moses` training tools, apart from the 4-gram target LM which was trained with the IRST LM Toolkit on 47 M running words.

MERT vs. amount of translation alternatives First, we tested whether and how the amount of translation alternatives generated by `Moses` impacts on the tuning. For this experiment the EuroParl task was selected. Several MERTs were performed constraining `Moses` to generate a different number of translations in each outer loop ($N = 100, 200, 400, 800$). The sets of weights obtained after each iteration of the outer loop are then used to translate the test set. Figure 6.4.1 shows the achieved BLEU score in the different conditions.

We observe that convergence is reached after few iterations (5-6). This fact is positive because it allows to run `Moses` only few times.

The weights obtained in the first iterations seem to award the use large N, but this effects vanishes very soon because the set of translation alternatives is continuously enlarged.

The final sets of weights perform very similar for each experimental condition; this is also positive because a limited number of N-best can be extracted, speeding up both the translation process and the inner loop.

MERT vs. amount of translation alternatives We also tested the impact of the size of the development set on the MERT procedure in both EuroParl and EPPS tasks. From the development set of the EuroParl we extracted 4 subsets of 100, 200 400 and 800 sentences, respectively. 529 sentences are randomly selected from the EPPS development set . The sets of weights obtained after each iteration of the outer loop are then used to translate the corresponding test sets.

Figures 6.4.1 and 6.4.1 show the achieved BLEU score in the different conditions for the EuroParl and EPPS tasks, respectively. Plots reveal that more stable and better results are obtained with weights optimized on larger dev set; moreover, EuroParl experiments show that

[1] http://www.tc-star.org

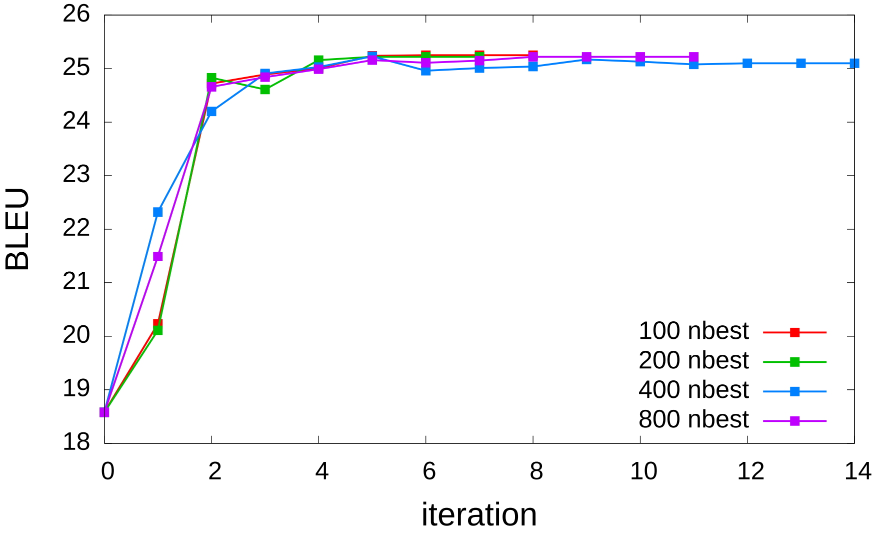


Figure 6.7: Performance (BLEU score) achieved on the EuroParl test set using feature weights optimized exploiting an increasing number of translation alternatives of the development set.

MERT with larger dev set tends to end in less iterations. In general, these experiments show that 2 iterations give the biggest relative improvement and that next iterations, which slightly improve on the dev set, are risky on the test set.

This behavior is explained by the tendency of MERT procedure to overfit the development data. Possible ways to limit the overfitting problems consists in enlarging the dev set and ending the tuning after few iterations. The former solution increases the time of tuning, while the latter make it faster and more robust. with respect to differences between dev and test sets. It is also trivial to stress that the development data should be as close as possible to the test domain.

Comparison of different optimization algorithm We also compared our optimization algorithm against the downhill simplex algorithm. For this experiment we employed `Moses` in the EPPS task.

Table 6.4.1 reports the increment of BLEU score achieved on the development and test sets after MERT; it shows that our approach is definitively competitive with (and slightly better than) the widely-used downhill simplex algorithm. The number of iterations to converge are similar, too. Moreover, the improvements achieved on the dev and test sets are comparable.

algorithm	iteration	Δ BLEU	
		dev	test
CLSP-WS	6	+3.2	+3.6
downhill simplex	7	+2.9	+3.4

Table 6.4: Performance improvement (absolute BLEU score) achieved on the EPPS task using two different optimization algorithm.

MERT vs. different input types Finally, we performed two separate MERT for the two input types handled by `Moses`, namely text and Confusion Networks. The human transcriptions (`verbatim`) and the CNs of the development data of the EPPS task were exploited.

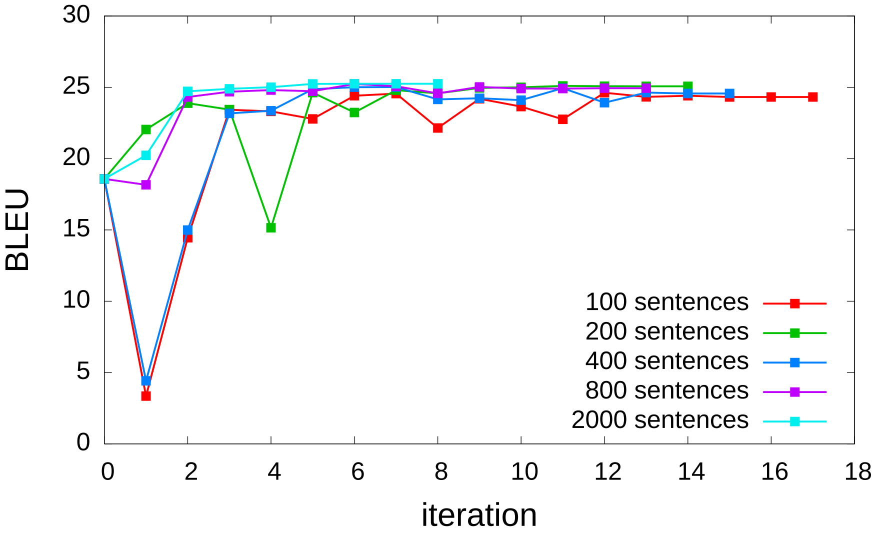


Figure 6.8: Performance (BLEU score) achieved on the EuroParl test set using feature weights optimized on development sets of increasing size.

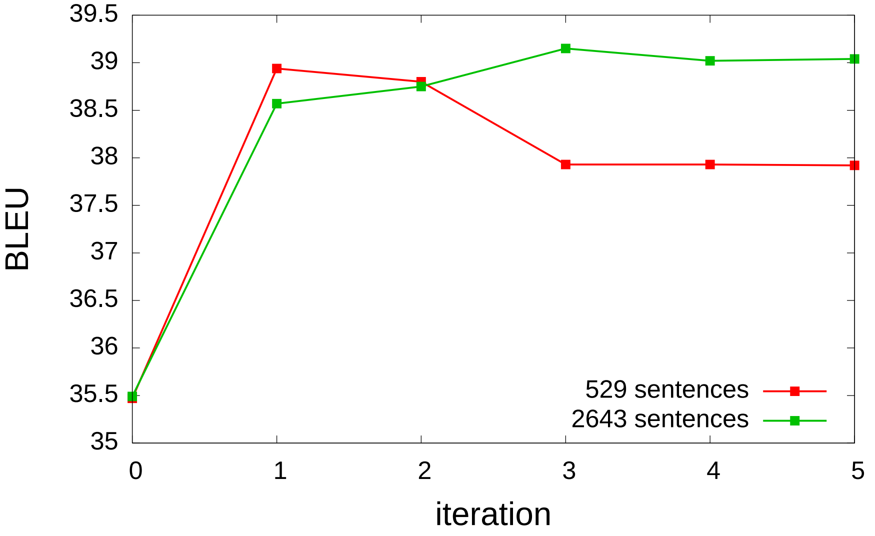


Figure 6.9: Performance (BLEU score) achieved on the EPPS test set using feature weights optimized on development sets of increasing size.

Weights optimized in the verbatim condition were applied to translate both human transcriptions (verbatim), the best automatic transcriptions (1-best), and the consensus decoding transcriptions (1-best-CN) extracted from the CNs Mangu et al. [2000] by taking the most probable words of each column. Weights optimized in the CN condition were applied to the CNs of the test set. The increments achieved on the development and test data are reported in Table 6.4.1.

input	Δ BLEU	
	dev	test
verbatim	+1.9	+2.1
1best	+2.1	+2.2
1best-CN	+1.6	+2.2
CN	+3.2	+3.6

Table 6.5: Performance improvement (absolute BLEU score) achieved on the EPPS task using different input types.

We observe that improvement on the test set ranges from 2.1 to 3.6 absolute BLEU points, and that it is consistent between dev and test. The bigger increase for the CNs is probably due to a choice of the initial set of weights performing worse than the corresponding set for the verbatim condition.

6.5 Efficient Language Model Handling

In this section we review main concepts related to the handling of language models (LMs) at run time, that is during the decoding phase. Concerning the estimation of language models the reader can refer to the documentation of publicly available tools, such as SRI LM Toolkit and the CMU-Cambridge SLM toolkit. These toolkits, in general, provide many methods for estimating n-gram probabilities and are capable of generating a static representation of an n-gram LM, a text or binary file, that can be used within other programs.

The motivation of developing software for handling LMs at run time is that efficiency, both in time and space, can be gained by exploiting peculiarities of the way they are used by the hosting program, namely the decoder.

The need for efficient LM handling comes from the intrinsic data-sparseness of language corpora. Empirically, for a given size of n-grams, the set of observations increases almost linearly with the size of the training data. Hence, the trend of using larger and larger training corpora compels for careful memory usage.

In general, to efficiently store observations and probabilities in a computer memory the following approaches can be tackled: pruning rare or unreliable observations, designing compact data-structures, and applying data compression. While the observation pruning is typically embedded in the tools to estimate the LMs, we focused on the other aspects, which are more related to the way the LM is used by a specific program.

In the following we discuss some of the features of our implementation: the representation of n-gram LMs, the quantization of probabilities, and the use of cache memories.

6.5.1 LM representation

In our implementation N-gram are stored in a data structure which indeed privileges memory saving rather than access time. In particular, single components of each n-grams are accessed via binary search and stored with 3 bytes, probabilities and back-off weights are instead stored

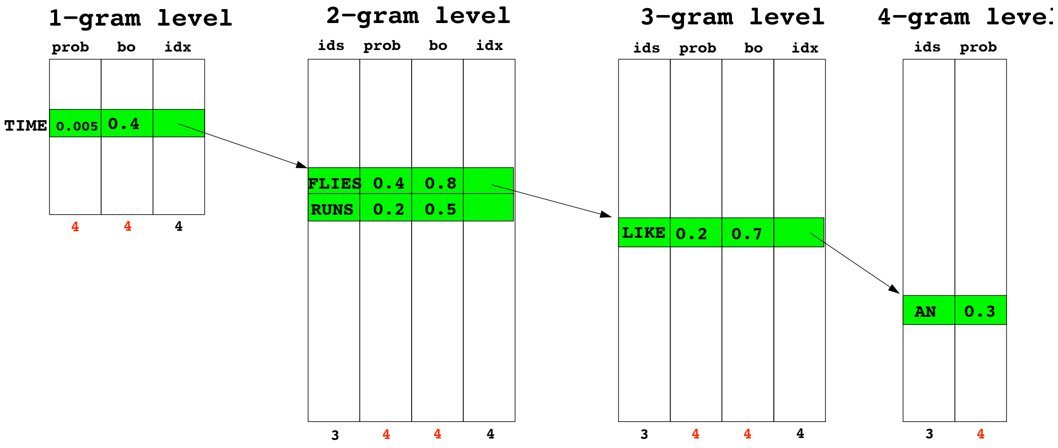


Figure 6.10: Data structure for storing n-gram language models.

in 4 bytes, namely floating point numbers. Improvements in memory savings are obtained by quantizing both back-off weights and probabilities.

6.5.2 Probability quantization

Quantization provides an effective way of reducing the number of bits needed to store floating point variables. The quantization process consists in partitioning the real space into a finite set of k quantization levels and identifying a center c_i for each level, $i = 1, \ldots, k$. A function $q(x)$ maps any real-valued point x onto its unique center c_i. Cost of quantization is the approximation error between x and c_i.

Previous experiments (cite) suggested us to apply the so-called binning method. The binning method partitions data points into uniformly populated intervals or *bins*. The center of each bin corresponds to the mean value of all points falling into it. If N_i is the number of points of the i-th bin, and x_i the smallest point in the i-th bin, a partition $[x_i, x_{i+1}]$ results such that N_i is constant for each $i = 0, \ldots, k-1$, where $x_k = 1$ by default. The following map is thus defined:

$$q(x) = c_i \text{ if } x_i <= x < x_{i+1}.$$

In particular, our implementation uses the following *greedy* strategy: bins are build by uniformly partition all different points of the data set. Finally, quantization is applied separately at each n-gram level and for each kind of score, that is probabilities or back-off weights. The level of quantization is set to 8 bits, that experimentally showed to cause no measurable loss in performance.

Quantization can be applied on any LM represented with the ARPA format. Quantized LMs can be converted into a binary format that can be efficiently uploaded at decoding time.

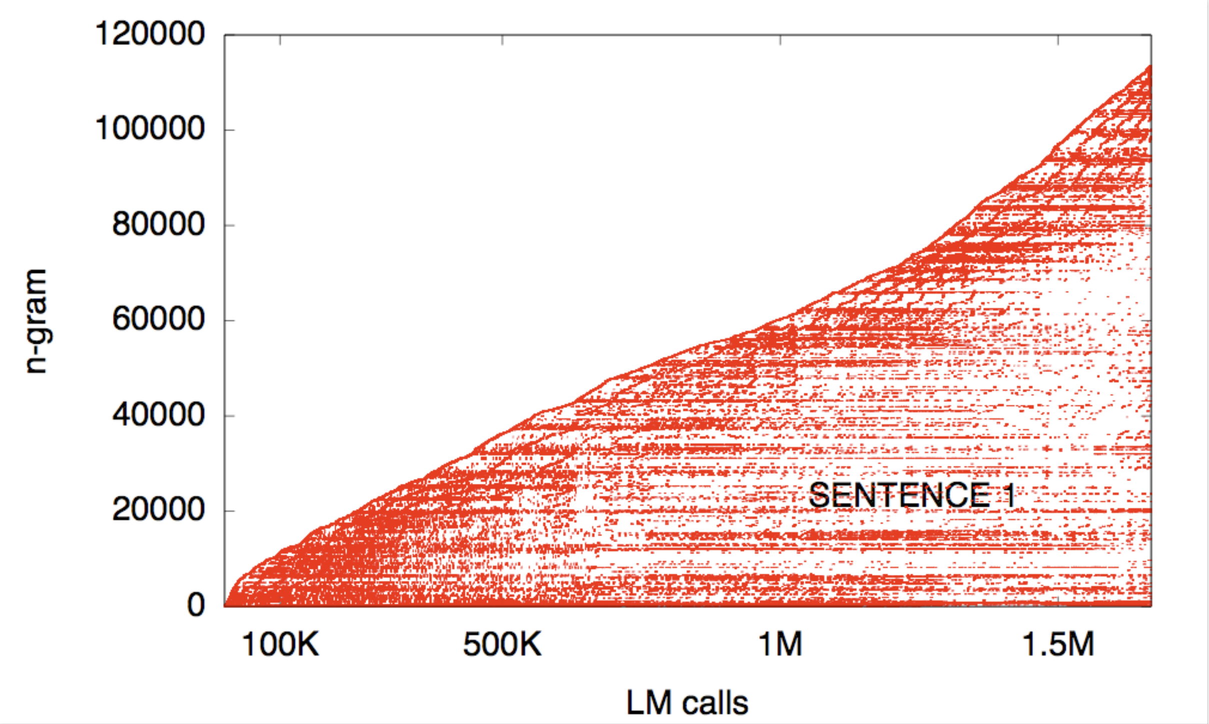


Figure 6.11: LM calls during decoding of a sentence by Moses.

6.5.3 Caching of probabilities

In order to overcome limitations of access time, caching is applied. The potential advantage of caching during MT decoding is made evident by the plot in Figure 6.11. It shows all calls of 3-gram probabilities by the search algorithm during the decoding of the following German sentence:

ich bin kein christdemokrat und glaube daher nicht an wunder . doch ich möchte dem europäischen parlament , so wie es gegenwürtig beschaffen ist , für seinen grossen beitrag zu diesen arbeiten danken.

During decoding of the sentence, about 120,000 different 3-grams are called for a total of about 1.7 million times. The fact that a relatively small subset of 3-grams is frequently accessed for each sentence suggest to store all of them into a cache. Each time a new sentence is decoded, the cache is reset and n-gram probabilities are added as soon as they are needed. Additional caches are also used to store LM states, and all partial n-grams searched in the data in order to limit the number of binary searches performed.

Chapter 7

Conclusions

The 2006 JHU Summer Workshop on statistical machine translation brought together efforts to build an open source toolkit and carry out research along two research goals: factored translation models and confusion network decoding.

We are optimistic that the toolkit will be the basis of much future research to improve statistical machine translation. Already during the workshop we received requests for Moses, and at the time of this writing the Moses web site[1] attracts 1000 visitors a month and a support mailing list gets a few emails a day. The performance of the system has been demonstrated, included by newcomers who took the software and obtained competitive performance at recent evaluation campaigns.

Our work of factored translation models has been demonstration not only in the experiments reported in this report, but also in follow-up work at our home instititions and beyond, resulting in publications in forthcoming conferences and workshops.

Our work on confusion network decoding has been demonstrated to be helpful to integrate speech recognition and machine translation, and even in more recent follow-up work, the integration of ambiguous morphological analysis tools to better deal with morphological rich languages.

While six weeks in summer in Baltimore seem like a short period of time, it was a focal point of many of our efforts and resulted in stimulating exchange of ideas and the establishment of lasting research relationships.

[1] http://www.statmt.org/moses/

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Appendix A

Follow-Up Research Proposal A Syntax and Factor Based Model for Statistical Machine Translation

This appendix contains Brooke Cowan's proposal for follow-on research, which was selected for additional funding by the National Science Foundation.

A.1 Introduction

This year's Summer Workshop on Language Engineering at Johns Hopkins University focused in part on the development of an open source toolkit for statistical machine translation (SMT). The toolkit's decoder, known as *Moses*, replicates the functionality exhibited by the phrase-based decoder Pharaoh (Koehn [2004]). One of the weaknesses of traditional phrase-based models is their inability to incorporate syntactic information in a direct and overt manner. For instance, most English sentences contain a subject and a verb, but there is no straightforward way to model this fact within the phrase-based framework. Furthermore, there are translation correspondences that are simple to describe using part-of-speech information but difficult to model using lexical items alone. (E.g., a French noun phrases that has the part-of-speech sequence *determiner noun adjective* will most likely in English be *determiner adjective noun.*) Moses addresses the latter problem by extending the phrase-based framework to include *factors*; hence, it exemplifies a *factor-based approach* to statistical machine translation. Factor-based models behave much like phrase-based models, but have the additional capability to take into account information such as morphology and parts of speech, lemmas, and phrase bracketing in the source and/or target languages during decoding.

The experimental results from this summer's workshop indicate that using factors can indeed improve translation performance. However, observation of Moses' translation output indicates that, even when BLEU scores improves, the system often does not adhere to basic global syntactic constraints[1] of the target language. We propose to address this problem by using a syntax-based system that explicitly models syntactic constraints in conjunction with the factor-based system developed this summer. A baseline version of the syntax-based system has been implemented at the Laboratory for Computer Science and Artificial Intelligence (CSAIL) at MIT (Cowan et al. [2006]). A fundamental component of this system is a discriminatively-trained model that takes as input a source-language parse tree and produces a detailed target-language syntactic structure called an *aligned extended projection*, or AEP. AEPs may include information

[1] We use the word *global* here to refer to properties that require examination of the clause in its entirety, such as *a clause will usually contain a finite verb* and *a clause will never have more than one finite verb.*

such as the main verb of the output sentence, the number and type of its arguments, and the correspondence (alignment) between source-side and target-side modifiers. The discriminative AEP model provides an extremely flexible framework for experimentation with a variety of language pairs and treebanking styles. Most importantly, it provides a framework for modeling global sytactic constraints of both the target language, as well as syntactic correspondences between the source and target language.

This proposal is structured as follows: we continue this section with some background on phrase-based and factor-based approaches to SMT; in Section A.2, we describe the syntax-based model in more detail; and in Section A.3, we outline the work that we propose to carry out this year to integrate the syntax-based and the factor-based models.

A.1.1 From Phrase-Based to Factor-Based Translation

Phrase-based systems (e.g., (Koehn [2004]; Koehn et al. [2003]; Och and Ney [2002, 2000])) advanced the state-of-the-art in statistical machine translation during the early part of this decade. They surpassed the performance of earlier models, proposed by researchers at IBM and known as the *IBM models* (Brown et al. [1993]), which used alignments between words (predicted using the EM algorithm) to estimate the values of translation parameters in a generative model. Phrase-based models combine the word alignments induced by the earlier SMT models to produce alignments between substrings of source and target text, which, in these models, are called *phrases*.[2] These phrasal translations, together with a search algorithm that looks for a high-scoring solution, form the basis of the phrase-based framework.

The current state-of-the-art phrase-based systems are log-linear models of the conditional probability of the target (e) given the source (f):

$$Pr(e|f) = \frac{\exp \sum_i \lambda_i h_i(e,f)}{\sum_{e'} \exp \sum_i \lambda_i h_i(e',f)} \tag{A.1}$$

The λ_i are weights on feature functions $h_i(e,f)$. The weights are usually trained using minimum error rate training (Och [2003]), although recently an online perceptron training algorithm has also been shown effective (Liang et al. [2006]). There are usually on the order of ten feature functions, among which may be

- bidirectional phrase models (models that score phrasal translations);
- bidirectional lexical models (models that consider the appearance of entries from a conventional translation lexicon in the phrasal translation);
- n-gram target-language models (n-th order Markov models whose parameters are trained on large amounts of monolingual data; the probability of each word in a phrase is conditioned on the preceding $n-1$ words, and the probability of the phrase is the product of the probabilities the words);
- distortion models (models that consider how source phrases get reordered in the translation).

Phrase-based models address a severe limitation of the early word-based models, which are restricted to many-to-one mappings between source and target words. This means that if the Spanish phrase *el libro del niño* were translated as *the boy's book* in the data, the pairing between *el libro* and *book* would be allowed when translating from Spanish to English, but not from English to Spanish. In contrast, phrase-based models allow for the alignment of multi-word

[2] Note that these phrases do not have to be phrases in any linguistic sense.

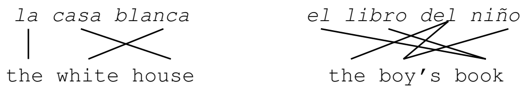


Figure A.1: When translating between Spanish and English, the positions of nouns and their modifying adjectives are usually swapped. Similarly, possessives in English generally precede nouns, whereas in Spanish they follow the noun.

units such as *the white house* with *la casa blanca*, *and so on and so forth* with *etcétera*, and *big crimes need* with *los grandes crímenes necesitan*.[3]

The use of many-to-many phrasal alignments means that these systems can capture some lexical reorderings as well as the translation of idiomatic expressions. For example, consider the phrasal translation pair *the white house* and *la casa blanca*. The positions of the English noun *house* and the adjective white are reversed relative to the positions of the Spanish noun casa and adjective *blanca*. Figure A.1 illustrates this swapping phenomenon. By learning that these phrases are common translations of one another, the system has a better chance of outputting the words in this phrase in the correct order. The IBM models have to learn how to reorder all of the words in the sentence as distinct units.

The generalization capabilities of phrase-based systems are limited due to their lack of direct, explicit knowledge of syntax. For example, as we have seen, Spanish adjectives tend to follow the noun they modify, a relative ordering that is the opposite of what is found in English. But while phrase-based models can model this swapping more easily than the IBM models can — by essentially memorizing these correspondences[4] — they have no mechanism for generalizing this phenomenon to novel input phrases. Hence, if the phrase *the purple apples* is seen during testing but not training, the system is forced to translate the words individually and relies on a different part of the system (i.e., another component model in the log-linear framework, such as the distortion model) to make a prediction about their relative order.

Factor-based translation is equipped to make this kind of generalization. These models can, for instance, make use of part-of-speech information to express the fact that, even though the purple apples has not been seen, the part-of-speech sequence determiner adjective noun has been seen, and quite often its translation has the part-of-speech sequence *determiner noun adjective*. Furthermore, if *the purple apple* has been seen, the framework has the ability to model the fact that *apple* is the lemma form of *apples*; the system can therefore make use of the translation *las manzanas moradas* to derive the singular version *la manzana morada*. More often than not, in the face of novel test strings, phrase-based systems to do not get the ordering correct.

Preliminary experimental results from this summer's workshop indicate that using factors can indeed improve translation performance. For instance, we ran a number of experiments at this summer's workshop that used morphological information when translating from English to Spanish. The morphological features we used included those shown in Table A.1. The use of the morphology improved the BLEU score by approximately 1.3 points over a phrase-based baseline (i.e., a model without any added factor information), from 23.41 to 24.66 BLEU. This gain was induced by using a language model trained with sequences in which the words of the original training data were replaced by strings representing their morphological features. During decoding, the factor-based model predicts the morphology of a translation hypothesis, and the score of the morphological language model is combined in the overall score of the hypothesis.

[3] Note that the final phrasal alignment involves phrases that cross syntactic phrasal boundaries. For example, *big crimes* is a noun phrase, and *need* is part of a verb phrase.

[4] The IBM models require the target phrase to be a single word and therefore cannot memorize such correspondences.

Category	Attributes
Adjective	gender, number
Determiner	gender, number, person, possessor
Noun	gender, number
Verb	gender, number, person, mode, tense
Pronoun	gender, number, person, case, possessor

Table A.1: The morphological features used in English-to-Spanish translation experiments with a factor-based model.

A.1.2 Motivation for a Syntax-Based Model

While factor-based models show tremendous promise in solving some of the gravest deficiencies of phrase-based systems, there remain some problems that are unlikely to be addressed. During decoding, the output of factor-based translation is constructed incrementally and left-to-right. These partial translations are also scored incrementally so as to make the computation tractable. This means that the component models $h_i(e, f)$ in equation A.1 cannot look globally at the translation to see whether it upholds global syntactic constraints of the target language. For instance, it is difficult to model the fact that in English, clauses usually have a single finite verb and a subject.

The output in Table A.2 is taken from a state-of-the-art phrase-based SMT system translating from German to English (the baseline system described in Collins et al. [2005]). This system has been trained using over 700K sentence pairs from the European Parliament dataset (Koehn [2005]). These examples represent a few of the syntactic errors this system tends to make. We consider each example in turn, discussing some, but not all, of the problems:

1:
- In the first clause, the substring *human rights practical* introduces an unlikely ordering of a noun phrase *human rights* and adjective *practical*.
- In the second clause, there are two finite verbs (*must* and *are*).

2:
- The clause beginning with *the convention...* introduces two adjacent noun phrases *...a draft a charter...*, which is an unlikely event.
- The prepositional phrase *in the hands of the council* appears before the verb it modifies (*laid*), which is unusual in English.
- The verb phrase *has formulated* has been split by elements that normally would not split a verb phrase.
- The adjective *remarkable* is following the noun *way*.
- There is a missing referring pronoun (*it*). I.e., the final part of the sentence should say something like *...laid it in the hands of the council*.

3:
- The infinitival phrase *to maintain* follows its noun phrase modifier.

4:
- The verb phrase *will...erected* is not syntactically well-formed (the insertion of the verb *be* would make it so).

5:
- The first part of the sentence could be rendered as two clauses *it seems to us the budget perspectives are not appropriate*, in which case there is a missing subject *it* and a missing verb *are*; alternatively, it could be rendered as a single clause *the budget perspectives seem to us not appropriate*, in which case the subject of the sentence has been placed after the verb, and there is lack of agreement between the subject and the verb.

Table A.2: Some examples of SMT output using a state-of-the-art phrase-based system from German to English.

SMT Output	**Reference Translation**
thus the implementation of human rights practical can be monitored , the union must have clear rules on possible penalties against the member states are available .	for the implementation of human rights to be monitored in practice also , however , the union must have clear rules regarding possible sanction mechanisms to be used against member states .
mr president , ladies and gentlemen , under the applause of the courts in luxembourg and strasbourg , the convention has a draft a charter of fundamental rights in a balanced way remarkable and formulated in the hands of the council laid .	mr president , ladies and gentlemen , with the approval of the courts in luxembourg and strasbourg , the convention has put together a draft charter of fundamental rights which is remarkably balanced , and has delivered it into the hands of the council .
i am with him that it is necessary , the institutional balance by means of a political revaluation of both the commission and the council to maintain .	i agree with him on the need to maintain the institutional balance and enhance the role , in political terms , of both the commission and the council .
irrespective of this , however , i should like to ask for this future is not already expect tomorrow , because they will gradually , stone for stone , erected .	that is why i invite you , in spite of everything , not to throw yourselves headlong into the future , as this is a future that should be built step by step , and stone by stone .
fifthly , seems to us the budget perspectives not appropriate...	fifthly , we also feel that the budgetary forecasts are not sufficient...

While this output is taken from a phrase-based, and not a factor-based, system, we argue that many of the syntactic errors, particularly those that are global in nature, will not be corrected by a factor-based system. For example, the misplacement of verbs with respect to their modifiers, as in examples 2 and 3, is a very common error. The problem stems from the fact that in independent clauses in German, the finite verb is placed in the second position of the sentence, and the infinitival verb, if it exists, is placed in the final position. This means that in the English translation, the infinitival verb may have to be moved across an arbitrary number of intervening modifiers. Since phrase-based (and factor-based) systems tend to either penalize translations that move phrases around too much or to explicitly limit the absolute distance that phrases can move (compromising the exactness of the search for efficiency), the output tends mimic the word ordering of the input.

Other elements such as subjects and objects may also need to be reordered to produce syntactically-sound output. Consider, for instance, translation of the following German sentence into English: *für seinen bericht möchte ich dem berichterstatter danken*. The English translation of this sentence, *i would like to thank the rapporteur for his report*, involves a considerable amount of reordering of the top-level phrases in the sentence (see Figure A.2): the subject *ich* moves from

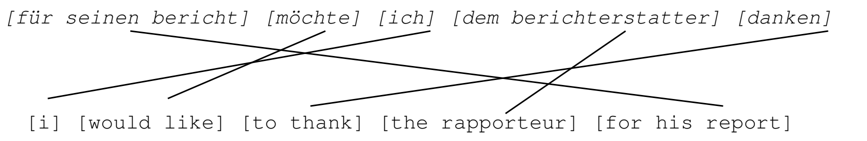

[für seinen bericht] [möchte] [ich] [dem berichterstatter] [danken]
[i] [would like] [to thank] [the rapporteur] [for his report]

Figure A.2: The relative positioning of the top-level (bracketed) phrases changes considerably in translation German to English.

[für seinen bericht] möchte [ich] [dem berichterstatter] danken

[ich] möchte [dem berichterstatter] [für seinen bericht] danken

[dem berichterstatter] möchte [ich] [für seinen bericht] danken

Figure A.3: In German, the top-level phrases can move around positionally in the sentence without significantly altering its meaning. In the example, the subject (*ich*), object (*dem berichterstatter*), and a prepositional-phrase modifier (*für seinen bericht*) exhibit such behavior.

after the German modal verb *möchte* to the front of the English translation; the prepositional-phrase modifier *für seinen bericht* moves from the front of the sentence to after the object in the English.

Figure A.3 shows three variations of the German sentence introduced above with roughly the same meaning, illustrating how the modifiers are relatively free to move around.[5] In contrast, the placement of phrases in English is generally more constrained: the subject of an English sentence is almost always placed before the verb; the object almost always comes after the verb. Hence, English is known as a predominantly subject-verb-object, or *S-V-O*, language. Therefore, when translating from German to English, there is likely to be quite a bit of reordering of top-level phrases.

The reordering of top-level phrases can also be quite common when translating between two fixed-word-order languages whose basic word orders differ. For instance, Turkish, Japanese, and Korean, among many of the world's other languages exhibit *subject-object-verb* word order. Figure A.4 shows how key sentential elements move around in languages with different basic word orders.

Reordering poses a considerable challenge for phrase-based translation systems. Factor-based systems have the potential to model reordering based on, for instance, part of speech rather than words (i.e., factor-based distortion models). Indeed, some recent work has in fact shown some improvement in translation quality by using part-of-speech information in the distortion model (Liang et al. [2006]). However, there are other global syntactic constraints concerning the presence of subjects, objects, verbs, and verbal modifiers, for instance, are difficult to enforce within the phrase-based framework, and will very likely be difficult to enforce within the factor-based framework as well. Our observations of output produced by Moses this summer are

[5] German is often characterized as a *V2* language due to the obligatory placement of the finite verb in the second position in declarative sentences.

S-O-V	(Japanese, Turkish, Korean,...)	George oranges eats
S-V-O	(English, Chinese, Spanish,...)	George eats oranges
V-S-O	(Arabic, Irish, Tagalog,...)	eats George oranges
O-S-V	(Xavante, Jamamadi,...)	oranges George eats

Figure A.4: The relative positions of the subject, verb, and object may be different for different languages.

consistent with this conjecture. For instance, missing verbs in sentences continues to be a problem with Moses, as it was with Pharaoh.

Our syntax-based model makes predictions about the roles of top-level phrases in the source-language input, as well as their positions in the target-language output. This approach directly addresses the global syntactic constraints, described above, which cannot easily be modeled by a factor-based model. We propose using this model to automatically reorder the input such that it more closely resembles the syntactic ordering of the target language; we also propose making use of the syntactic role information (e.g., *subject*, object, etc.) that the model predicts to better constrain the output of the factor-based system. Finally, by translating certain parts of the sentence prior to using the factor-based system, we intend to ensure that certain essential parts of the sentence (such as the verb, any wh-words or complementizers, etc.) appear in the output. Before providing a detailed outline of our proposed integrated syntax and factor based system, we describe our syntax-based model.

A.2 The Syntax-Based Component

This section is based on work we have done at MIT CSAIL on a framework for *tree-to-tree* based statistical translation (Cowan et al. [2006]). We focus here on one component of this framework: a model that predicts *aligned extended projections*, or AEPs. AEPs are derived from the concept of an *extended projection* in lexicalized tree adjoining grammars (LTAG) (Frank [2002]), with the addition of alignment information that is based on work in synchronous LTAG (Shieber and Schabes [1990]). The AEP model maps parse trees in the source language to parse trees in the target language. We use a feature-based model with a perceptron learning algorithm to learn this mapping. The model is learned from a corpus of translation pairs, where each sentence in the source or target language has an associated parse tree. We see two major benefits of tree-to-tree based translation. First, it is possible to explicitly model the syntax of the target language, thereby improving grammaticality. Second, we can build a detailed model of the correspondence between the source and target parse trees, thereby attempting to construct translations that preserve the meaning of source language sentences.

Our AEP prediction framework involves a two-step process (described below). We will use the German sentence *wir wissen daß das haupthemmnis der vorhersehbare widerstand der hersteller war* as a running example. For this example we take the desired translation to be *we know that the main obstacle has been the predictable resistance of manufacturers.*

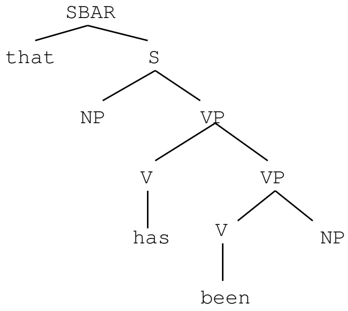
Step 1: The German sentence is parsed and then broken down into separate parse structures for a sequence of clauses. For example, the German example above is broken into a parse structure for the clause *wir wissen* followed by a parse structure for the subordinate clause *daß...war.*

Step 2: An AEP is predicted for each German clause. To illustrate this step, consider translation of the second German clause, which has the following parse structure:

```
s-oc kous-cp daß
     np-sb$\boxed{1}$ art das
             nn haupthemmnis
     np-pd$\boxed{2}$ art der
             adja vorhersehbare
             nn widerstand
             np-ag art der
                   nn hersteller
     vafin-hd war
```

Note that we use the symbols $\boxed{1}$ and $\boxed{2}$ to identify the two modifiers (arguments or adjuncts) in the clause, in this case a subject and an object.

A major part of the AEP is a parse-tree fragment, that is similar to a TAG elementary tree (see also Figure A.5):



Following the work of Frank [2002], we will refer to a structure like this as an *extended projection* (EP). The EP encapsulates the core syntactic structure in the English clause. It contains the main verb *been*, as well as the function words that and *has*. It also contains a parse tree "spine" which has the main verb *been* as one of its leaves, and has the clause label `SBAR` as its root. In addition, it specifies positions for arguments in the clause—in this case NPs corresponding to the subject and object.

An AEP contains an EP, as well as *alignment information* about where the German modifiers should be placed in the extended projection. For example, the AEP in this case would contain the tree fragment shown above, together with an alignment specifying that the modifiers $\boxed{1}$ and $\boxed{2}$ from the German parse will appear in the EP as subject and object, respectively. In summary, an AEP encapsulates the core syntactic structure of the English clause, as well as information about where the translations of German modifiers should appear.

AEPs are detailed structural objects, and their relationship to the source-language clause can be quite complex. We use a discriminative feature-based model, trained with the perceptron algorithm, to incrementally predict the AEP in a sequence of steps. At each step we define features that allow the model to capture a wide variety of dependencies within the AEP itself, or between the AEP and the source-language clause.

A.2.1 Aligned Extended Projections (AEPs)

We now provide a detailed description of AEPs. Figure A.5 shows examples of German clauses paired with the AEPs found in training data.[6] The German clause is assumed to have n (where $n \geq 0$) modifiers. For example, the first German parse in Figure A.5 has two arguments, indexed as 1 and 2. Each of these modifiers must either have a translation in the corresponding English clause, or must be deleted.

An AEP consists of the following parts:[7]

STEM: A string specifying the stemmed form of the main verb in the clause.

[6] Note that in this work we consider translation from German to English; in the remainder of the section we take English to be synonymous with the target language in translation and *German* to be synonymous with the source language.

[7] Note that the variables `STEM`, `SPINE`, `VOICE`, `WH`, `MODALS`, and `INFL` essentially describe the EP of the English main verb in the clause; the remaining variables `SUBJECT`, `OBJECT`, and `MOD(i)` specify the position of modifiers in the German clause.

German Clause	English AEP
s-oc kous-cp daß np-sb$\boxed{1}$ art das nn haupthemmnis np-pd$\boxed{2}$ art der adja vorhersehbare nn widerstand np-ag art der nn hersteller vafin-hd war Paraphrase: *that [np-sb the main obstacle] [np-pd the predictable resistance of manufacturers] was*	STEM: be SPINE: SBAR-A IN that S NP-A VP V NP-A VOICE: active SUBJECT: $\boxed{1}$ OBJECT: $\boxed{2}$ MODALS: has INFL: been
s pp-mo$\boxed{1}$ appr zwischen piat beiden nn gesetzen vvfin-hd bestehen adv-mo$\boxed{2}$ also np-sb$\boxed{3}$ adja erhebliche adja rechtliche $, , adja praktische kon und adja wirtschaftliche nn unterschiede Paraphrase: *[pp-mo between the two pieces of legislation] exist so [np-sb significant legal, practical and economic differences]*	STEM: be SPINE: S NP-A VP V NP-A VOICE: active SUBJECT: “there” OBJECT: $\boxed{3}$ MODALS: NULL INFL: are MOD1: post-verb MOD2: pre-sub
s-rc prels-sb die vp pp-mo$\boxed{1}$ appr an pdat jenem nn tag pp-mo$\boxed{2}$ appr in ne tschernobyl vvpp-hd gezündet vafin-hd wurde Paraphrase: *which [pp-mo on that day] [pp-mo in chernobyl] released were*	STEM: release SPINE: SBAR WHNP SG-A VP V VOICE: passive WH: which MODALS: was INFL: released MOD1: post-verb MOD2: post-verb

Figure A.5: Three examples of German parse trees, together with their aligned extended projections (AEPs) in the training data. Note that AEP elements whose value is *null* are not shown.

SPINE: A syntactic structure associated with the main verb. The structure has the symbol `V` as one of its leaf nodes; this is the position of the main verb. It includes higher projections of the verb such as VPs, Ss, and SBARs. It also includes leaf nodes `NP-A` in positions corresponding to noun-phrase arguments (e.g., the subject or object) of the main verb. In addition, it may contain leaf nodes labeled with categories such as `WHNP` or `WHADVP` where a wh-phrase may be placed. It may include leaf nodes corresponding to one or more complementizers (common examples being *that*, *if*, *so that*, and so on).

VOICE: One of two alternatives, `active` or `passive`, specifying the voice of the main verb.

SUBJECT: This variable can be one of three types. If there is no subject position in the `SPINE` variable, then the value for `SUBJECT` is `NULL`. Otherwise, `SUBJECT` can either be a string, for example *there*,[8] or an index of one of the n modifiers in the German clause.

OBJECT: This variable is similar to `SUBJECT`, and can also take three types: `NULL`, a specific string, or an index of one of the n German modifiers. It is always `NULL` if there is no object position in the `SPINE`; it can never be a modifier index that has already been assigned to `SUBJECT`.

WH: This variable is always `NULL` if there is no wh-phrase position within the `SPINE`; it is always a non-empty string (such as *which*, or *in which*) if a wh-phrase position does exist.

MODALS: This is a string of verbs that constitute the modals that appear within the clause. We use `NULL` to signify that there are no modals.

INFL: The inflected form of the verb.

MOD(i): There are n modifier variables `MOD(1), MOD(2), ..., MOD(n)` that specify the positions for German arguments that have not already been assigned to the `SUBJECT` or `OBJECT` positions in the spine. Each variable `MOD(i)` can take one of five possible values:

- `null`: This value is chosen if and only if the modifier has already been assigned to the subject or object position.
- `deleted`: This means that a translation of the i'th German modifier is not present in the English clause.
- `pre-sub`: The modifier appears after any complementizers or wh-phrases, but before the subject of the English clause.
- `post-sub`: The modifier appears after the subject of the English clause, but before the modals.
- `in-modals`: The modifier appears after the first modal in the sequence of modals, but before the second modal or the main verb.
- `post-verb`: The modifier appears somewhere after the main verb.

[8] This happens in the case where there exists a subject in the English clause but not in the German clause. See, for instance, the second example in Figure A.5.

A.2.2 A Discriminative Model for AEP Prediction

In this section we describe linear history-based models with beam search, and the perceptron algorithm for learning in these models. These methods will form the basis for our model that maps German clauses to AEPs.

We have a training set of n examples, (x_i, y_i) for $i = 1 \dots n$, where each x_i is a German parse tree, and each y_i is an AEP. We follow previous work on history-based models, by representing each y_i as a series of N decisions $\langle d_1, d_2, \dots d_N \rangle$. In our approach, N will be a fixed number for any input x: we take the N decisions to correspond to the sequence of variables `STEM, SPINE, ..., MOD(1), MOD(2), ..., MOD(n)` described in section A.2.1. Each d_i is a member of a set $\mathcal{D}_i$ which specifies the set of allowable decisions at the i'th point (for example, $\mathcal{D}_2$ would be the set of all possible values for `SPINE`). We assume a function ADVANCE$(x, \langle d_1, d_2, \dots, d_{i-1} \rangle)$ which maps an input x together with a prefix of decisions $d_1 \dots d_{i-1}$ to a subset of $\mathcal{D}_i$. ADVANCE is a function that specifies which decisions are allowable for a past history $\langle d_1, \dots, d_{i-1} \rangle$ and an input x. In our case the ADVANCE function implements hard constraints on AEPs (for example, the constraint that the `SUBJECT` variable must be `NULL` if no subject position exists in the `SPINE`). For any input x, a *well-formed* decision sequence for x is a sequence $\langle d_1, \dots, d_N \rangle$ such that for $i = 1 \dots n$, $d_i \in$ ADVANCE$(x, \langle d_1, \dots, d_{i-1} \rangle)$. We define GEN$(x)$ to be the set of all decision sequences (or AEPs) which are well-formed for x.

The model that we will use is a discriminatively-trained, feature-based model. A significant advantage to feature-based models is their flexibility: it is very easy to sensitize the model to dependencies in the data by encoding new features. To define a feature-based model, we assume a function $\bar{\phi}(x, \langle d_1, \dots, d_{i-1} \rangle, d_i) \in \mathbb{R}^d$ which maps a decision d_i in context $(x, \langle d_1, \dots, d_{i-1} \rangle)$ to a feature vector. We also assume a vector $\bar{\alpha} \in \mathbb{R}^d$ of parameter values. We define the *score* for any partial or complete decision sequence $y = \langle d_1, d_2, \dots, d_m \rangle$ paired with x as:

$$\text{SCORE}(x, y) = \Phi(x, y) \cdot \bar{\alpha} \tag{A.2}$$

where $\Phi(x, y) = \sum_{i=1}^{m} \bar{\phi}(x, \langle d_1, \dots, d_{i-1} \rangle, d_i)$. In particular, given the definitions above, the output structure $F(x)$ for an input x is the highest–scoring well–formed structure for x:

$$F(x) = \arg \max_{y \in \text{GEN}(x)} \text{SCORE}(x, y) \tag{A.3}$$

To decode with the model we use a beam-search method. The method incrementally builds an AEP in the decision order $d_1, d_2, \dots, d_N$. At each point, a beam contains the top M highest–scoring partial paths for the first m decisions, where M is taken to be a fixed number. The score for any partial path is defined in Eq. A.2. The ADVANCE function is used to specify the set of possible decisions that can extend any given path in the beam.

To train the model, we use the averaged perceptron algorithm described by Collins [2002]. This combination of the perceptron algorithm with beam-search is similar to that described by Collins and Roark [2004].[9] The perceptron algorithm is a convenient choice because it converges quickly — usually taking only a few iterations over the training set (Collins [2002]; Collins and Roark [2004]).

A.2.3 The Features of the Model

The model's features allow it to capture dependencies between the AEP and the German clause, as well as dependencies between different parts of the AEP itself. The features included in $\bar{\phi}$ can consist of any function of the decision history $\langle d_1, \dots, d_{i-1} \rangle$, the current decision d_i, or the German clause. In defining features over AEP/clause pairs, we make use of some basic

[9] Future work may consider alternative algorithms, such as those described by Daumé and Marcu [2005].

functions which look at the German clause and the AEP (see Tables A.3 and A.4). We use various combinations of these basic functions in the prediction of each decision d_i, as described below.

1	main verb
2	any verb in the clause
3	all verbs, in sequence
4	spine
5	tree
6	preterminal label of left-most child of subject
7	terminal label of left-most child of subject
8	suffix of terminal label of right-most child of subject
9	preterminal label of left-most child of object
10	terminal label of left-most child of object
11	suffix of terminal label of right-most child of object
12	preterminal label of the negation word *nicht* (*not*)
13	is either of the strings *es gibt* (*there is/are*) or *es gab* (*there was/were*) present?
14	complementizers and wh-words
15	labels of all wh-nonterminals
16	terminal labels of all wh-words
17	preterminal label of a verb in first position
18	terminal label of a verb in first position
19	terminal labels of all words in any relative pronoun under a PP
20	are all of the verbs at the end?
21	nonterminal label of the root of the tree
22	terminal labels of all words constituting the subject
23	terminal labels of all words constituting the object
24	the leaves dominated by each node in the tree
25	each node in the context of a CFG rule
26	each node in the context of the RHS of a CFG rule
27	each node with its left and right sibling
28	the number of leaves dominated by each node in the tree

Table A.3: Functions of the German clause used for making features in the AEP prediction model.

1	does the SPINE have a subject?
2	does the SPINE have an object?
3	does the SPINE have any wh-words?
4	the labels of any complementizer nonterminals in the SPINE
5	the labels of any wh-nonterminals in the SPINE
6	the nonterminal labels SQ or SBARQ in the SPINE
7	the nonterminal label of the root of the SPINE
8	the grammatical category of the finite verbal form INFL (i.e., infinitive, 1st-, 2nd-, or 3rd-person pres, pres participle, sing past, plur past, past participle)

Table A.4: Functions of the English AEP used for making features in the AEP prediction model.

STEM: Features for the prediction of STEM conjoin the value of this variable with each of the functions in lines 1–13 of Table A.3. For example, one feature is the value of STEM conjoined with the main verb of the German clause. In addition, $\bar{\phi}$ includes features sensitive to the rank of a candidate stem in an externally-compiled lexicon.[10]

SPINE: Spine prediction features make use of the values of the variables SPINE and STEM from the AEP, as well as functions of the spine in lines 1–7 of Table A.4, conjoined in various ways with the functions in lines 4, 12, and 14–21 of Table A.3. Note that the functions in Table A.4 allow us to look at substructure in the spine. For instance, one of the features for SPINE is the label SBARQ or SQ, if it exists in the candidate spine, conjoined with a verbal preterminal label if there is a verb in the first position of the German clause. This feature captures the fact that German yes/no questions begin with a verb in the first position.

VOICE: Voice features in general combine values of VOICE, SPINE, and STEM, with the functions in lines 1–5, 22, and 23 of Table A.3.

SUBJECT: Features used for subject prediction make use of the AEP variables VOICE and STEM. In addition, if the value of SUBJECT is an index i (see section A.2.1), then $\bar{\phi}$ looks at the nonterminal label of the German node indexed by i as well as the surrounding context in the German clausal tree. Otherwise, $\bar{\phi}$ looks at the value of SUBJECT. These basic features are combined with the functions in lines 1, 3, and 24–27 of Table A.3.

OBJECT: We make similar features to those for the prediction of SUBJECT. In addition, $\bar{\phi}$ can look at the value predicted for SUBJECT.

WH: Features for WH look at the values of WH and SPINE, conjoined with the functions in lines 1, 15, and 19 of Table A.3.

MODALS: For the prediction of MODALS, $\bar{\phi}$ looks at MODALS, SPINE, and STEM, conjoined with the functions in lines 2–5 and 12 of Table A.3.

INFL: The features for INFL include the values of INFL, MODALS, and SUBJECT, and VOICE, and the function in line 8 of Table A.4.

MOD(i): For the MOD(i) variables, $\bar{\phi}$ looks at the value of MODALS, SPINE and the current MOD(i), as well as the nonterminal label of the root node of the German modifier being placed, and the functions in lines 24 and 28 of Table A.3.

A.2.4 Experiments with the AEP Model

We implemented an end-to-end system for translation from German to English using our AEP prediction model as a component. The Europarl corpus (Koehn [2005]) constituted our training data. This corpus contains over 750,000 training sentences; we extracted over 441,000 training examples for the AEP model from this corpus (see (Cowan et al. [2006]) for details on the extraction of these training examples). We reserved 35,000 of these training examples as development data for the model. We used a set of features derived from the those described in

[10] The lexicon is derived from GIZA++ and provides, for a large number of German main verbs, a ranked list of possible English translations.

section A.2.3. This set was optimized using the development data through experimentation with several different feature subsets.

Modifiers within German clauses were translated using the phrase-based model of Koehn et al. [2003]. We first generated n-best lists for each modifier. We then built a reranking model to choose between the elements in the n-best lists. The reranker was trained using around 800 labeled examples from a development set.

The test data for the experiments consisted of 2,000 sentences, and was the same test set as that used by Collins et al. [2005]. We use the model of Koehn et al. [2003] as a baseline for our experiments. The AEP-driven model was used to translate all test set sentences where all clauses within the German parse tree contained at least one verb and there was no embedding of clauses—there were 1,335 sentences which met these criteria. The remaining 665 sentences were translated with the baseline system. This set of 2,000 translations had a BLEU score (Papineni et al. [2002]) of 23.96. The baseline system alone achieved a BLEU score of 25.26 on the same set of 2,000 test sentences. We also obtained judgments from two human annotators on 100 randomly-drawn sentences on which the baseline and AEP-based outputs differed. For each example the annotator viewed the reference translation, together with the two systems' translations presented in a random order. Annotator 1 judged 62 translations to be equal in quality, 16 translations to be better under the AEP system, and 22 to be better for the baseline system. Annotator 2 judged 37 translations to be equal in quality, 32 to be better under the baseline, and 31 to be better under the AEP-based system.

A.3 A Syntax and Factor Based Model for SMT

In the preceding section, we presented a model that predicts detailed target-language syntactic structures, which include constraints on the alignments between source and target parse trees. In this work, we intend to implement a model that integrates our syntax-based system and the factor-based system Moses. The integration involves using the syntax-based system to predict the syntactic roles of constituents in the source-language input, and reorder them before they are translated using Moses. In addition, the syntax-based system would be used to translate certain parts of the input and ensure that they appear in the target language output. We would like to test this integrated model with German-to-English translation, as well as Spanish-to-English and English-to-Spanish translation. The work with Spanish and English will form a natural continuation of the work we performed translating from English to Spanish this summer at the workshop. Although the primary focus of this work will be on the integration with Moses, we see the need for improvement of our AEP model. We hope such improvements will contribute to better quality translations produced by the integrated system. Finally, we envision implementation of a few alternative approaches to end-to-end translation using the AEP model; we expect to use these alternatives as points of comparison with the integrated approach. The next few sections describe our proposed integration with Moses, some additional motivations for investigating Spanish-English translation, the AEP-prediction improvements that we anticipate carrying out, and the alternative end-to-end translation systems.

A.3.1 Integration with a Factor-Based System

The end-to-end translation framework we have developed in previous work uses a phrase-based system to produce n-best lists of modifier translations, which are then reranked and placed into the final translation. By selecting modifier translations independently, we are failing to make use of valuable contextual information that could be used to form better translations. Rather than produce modifier translations in isolation, we can use the syntax-based system to produce modified MT input to the phrase-based system. Figure A.6 illustrates how the input to the MT

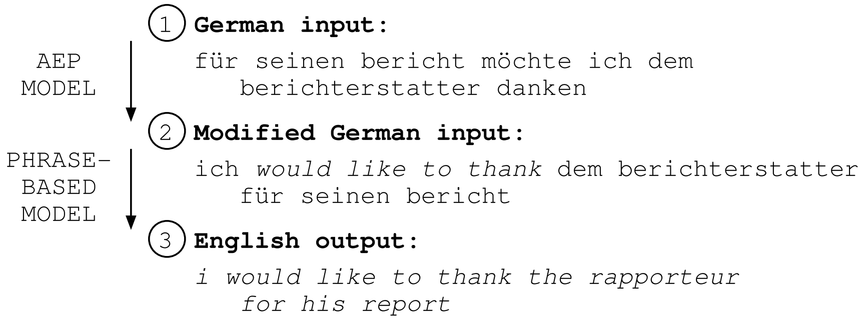

1 German input:
für seinen bericht möchte ich dem berichterstatter danken
AEP MODEL
2 Modified German input:
ich would like to thank dem berichterstatter für seinen bericht
PHRASE-BASED MODEL
3 English output:
i would like to thank the rapporteur for his report

Figure A.6: The input to the MT system — *für seinen bericht möchte ich dem berichterstatter danken* — is rearranged by the syntax-based system to produced modified input to the phrase-based system.

system is rearranged by the syntax-based AEP model. Note that in step two of the figure, some of the input has been translated to English (the verb sequence *would like to thank*), while some if it has merely been reordered. This allows the phrase-based system to decode the entire AEP at once.

An approach similar to this one has been investigated in previous work using hand-written reordering rules, which improved translation quality when compared with a phrase-based baseline system (Collins et al. [2005]). Our current work differs from the previous work in several significant ways:

- our work is carried out entirely within a statistical framework, whereas the earlier work used hand-coded deterministic rules for reordering;
- our work attempts to identify the roles of target-language output phrases and account for them in the source-language input, whereas the previous work attempted only to reorder the input; the prediction of grammatical functions such as *subject* and object can be used as additional input to the phrase-based system (see below);
- our work explicitly tries to account for the existence and translation of certain sentence elements such as complementizers, wh-words, and main verbs;

In addition to the simple reordering of input suggested in Figure A.6, we envision several extensions. We might, for instance, try training language models specific to the syntactic roles predicted by the AEP model (e.g., subject, object, verbal modifier). These language models could be incorporated into the factor-based framework as additional features in the model. The use of such language models would be motivated by the desire to have the model learn something about the structure of a "subject", for instance (e.g., that a subject should probably look like a noun phrase).

This particular line of investigation raises many interesting research questions related to the reordering of top-level phrases (i.e., modifiers):

- Does it help to disallow reordering of the top-level phrases in the modified input to the phrase-based system (i.e., implement a hard constraint on reordering)? Or, is it better to implement a soft constraint on reordering (for example by penalizing the reordering of modifiers)? Or, is it better not to impose any constraints on reordering at all?
- How much language engineering is necessary to extract a reasonable subset of possible permutations of top-level phrases in the input? How well can the phrase-based decoder do by simply taking into account all possible reorderings while decoding? (Note that if

arbitrary reorderings of words in the sentence are allowed, the decoding problem is NP-complete (Knight [1999]).) Do we really need to use a full parse, or can we devise a model that uses only syntactic chunking (partial parsing) or semantic role labeling?

- Can we simplify the role of the first (preprocessing) step, perhaps by (1) learning a mapping from source-sentence elements to target-sentence roles (subject, object, modifier, verb, complementizer), and then (2) learning an ordering on those elements? Note that this approach implies that no part of the input to the phrase-based system would be translated by the syntax-based system.

A.3.2 Other Language Pairs: Spanish/English

We would like to test the integrated syntax and factor based system with language pairs other than German/English, and for translation into a language besides English. One language pair that we are interested in working with is Spanish/English. Spanish is interesting for a number of reasons (Zagona [2002]):

- it has a fairly rich morphology, with subjects and verbs agreeing in number and person, and the nouns, determiners, and adjectives in a noun phrase agreeing in number and gender;
- constituent order is not fixed in declarative sentences (constituents may appear as S-V-O, V-O-S, or V-S-O);
- if understood from context, the subject does not have to appear in a sentence;
- the use of the subjunctive mood is quite prevalent and may be triggered by a phrase that appears far away from the inflected verb;
- the passive voice is used in many cases where active voice would be the natural choice in English;
- Spanish uses two forms of past tense (preterite and imperfect) where English uses only one (simple);
- Spanish has two forms of the verb *to be*;
- Spanish uses double clitics (that is, two clitics with the same referent), and there are two possible positions when placing clitics in sentences where a verb appears in the progressive or infinitive form.

From a research perspective, one of the benefits of our approach is that we can leverage the relatively recent advances in parsing languages other than English (e.g., (Chiang and Bikel [2002]; Arun and Keller [2004]; Collins et al. [1999]; Cowan and Collins [2005])). We have developed a statistical parser for Spanish (Cowan and Collins [2005]) that we intend to use for this project. The parser makes use of morphological information and reranking techniques to achieve, on test data, an F1 score of 85.1% in the recovery of labeled constituents. The parser is currently trained on only 2800 sentences; this number will increase by a factor of 10 with the release of new data at the end of 2006.

A.3.3 Improved AEP Prediction

Improvements in the accuracy with which the AEP model predicts AEPs will almost certainly lead to improved translation quality, and can only reduce the amount of work that the factor-based system has to do. We have analyzed several random samples of output from our current system in an attempt to characterize its current performance. Table A.5 shows examples of some of the errors we have observed:

1. **subject/verb agreement**: In English, the subject and verb must agree in number. In the example, the verb *to be* is inflected for plurality, while the subject is singular.

2. **subject choice**: The AEP model predicts there is no subject, or mispredicts the alignment of the subject. In the example, the second clause of the sentence (*while believe on the same side of the political spectrum*) is missing a subject.

3. **object choice**: The AEP model predicts there is no object, or (more commonly) mispredicts the alignment of the object. In the example, the true object — *position* — in the last clause (*to take in his second speech to this issue position*) is incorrectly predicted as a modifier and is placed after the object.

4. **number finite verbs**: The system occasionally produces more than one finite verb per clause. In the example, the final clause (*we will come in future this is often*) contains two finite verbs, *come* and *is*. The reason for this is usually that the phrase-based system introduces a new finite verb in translating of one of the modifiers.

5. **preposition choice**: Either a preposition is missing, or the choice of preposition is incorrect. In the example, the preposition *at* has been selected; a more appropriate choice would have been *on*.

It is clear from this list that the prediction of particular parts of the AEP could be improved. For instance, subjects and objects are often not accurately predicted. In addition, we have routinely observed that the choice of the main verb is often not optimal or even correct. Based on our informal observations, it seems to be the case that high-accuracy AEP prediction is correlated with high-accuracy translation output. We intend to produce by hand a set of gold standard AEPs which could be used to generate and score translations. The difference between generating translations using the gold-standard AEPs and generating translations using the predicted AEPs will give us a more quantitative idea of the loss incurred by the mispredictions.

The feature-driven approach allows a wide range of features to be tested in attempting to improve AEP prediction accuracy. For example, it would be relatively easy to incorporate a syntactic language model (i.e., a prior distribution over AEP structures) induced from a large amount of English monolingual data. Future work may also consider alternative definitions of AEPs. For example, we might consider AEPs that include larger chunks of phrase structure, or we might consider AEPs that contain more detailed information about the relative ordering of modifiers.

Alternative learning methods might improve the accuracy of the model. For example, a large-margin optimization technique such as the exponentiated gradient approach to structured prediction (Bartlett et al. [2004]) might be adapted to the AEP prediction problem. We might also look into improving how training examples are extracted, for instance, by looking into a better method for extracting and aligning clause pairs and modifiers. Our current method involves heuristics for determining modifier alignment; this might be done instead by using the EM algorithm to induce the best alignment.

A.3.4 Alternative End-to-End Systems

We foresee implementing at least two alternative translation systems using our AEP model. One of these systems uses finite state machines to represent alternative modifier translations; it is closer in nature to our current modifier-reranking framework, although we have reason to

Table A.5: Examples of some common errors in the output of our syntax-based system.

Error Type	**System Output**	**Reference Translation**
subject/verb agreement	the council are denied any power of legislating .	the council is denied any power of legislating .
subject choice	mr blair sees the precondition for more liberalisation while believe on the same side of the political spectrum , this is the prerequisite for the development of a social europe	mr blair sees this as the condition for greater liberalisation , while others , on the same side of the political chessboard , believe that it is the condition for the advent of social europe
object choice	i hope very that the prime minister sets it positive apart and would ask him if it does to take in his second speech to this issue position	i would like to hope that the prime minister will address it positively and i should like , if he can , for him to take a position on this issue in his second speech .
number finite verbs	this annex is and i know we will come in future this is often	this is to be welcomed , and i know we will return to this many times in the future .
preposition choice	i should like to comment at the thessaloniki agenda in the areas of immigration and asylum	mr president , i am going to refer to the thessaloniki agenda in relation to immigration and asylum .

believe it will perform better than our current implmentation. The other alternative involves a recursive application of the AEP model to modifier translation.

Using finite state machines Rather than using the phrase-based system to produce n-best lists of translations, we can use it to produce finite state machines (FSM) representing a network of possible translations (see, e.g., (Mohri [1997])). It is then easy to create an integrated AEP-FSM, in which the conjunctions and other substrings of the translation derived from the AEP are also represented as finite-state machines. We could then take the intersection of the AEP-FSM with an n-gram language model, for instance. Selecting modifiers using this representation would correspond to searching the finite-state network for the most likely path. Crucially, this search would take into account the contextual information that is being thrown away in our current reranking approach. It would also incorporate a language model over the entire sentence. The current system uses a language model only when producing modifier translation candidates with the phrase-based system. Finally, the FSM framework facilitates the incorporation of any additional models that can be encoded using a finite-state representation. For instance, we might train language models for particular types of modifiers predicted by the AEP (e.g., subject, object, etc).

Recursive prediction of modifier AEPs According to most (if not all) syntactic theories, classes of words other than verbs (such as nouns, adjectives, and prepositions) can also subcategorize lexically for certain types of arguments, and can influence their distributions (Haegeman and Guéron [1999]). Similarly, extended projections may be formed for many types of words besides verbs. A natural extension to the current AEP model, then, is the application of AEP prediction to the translation of modifiers. For example, given a German modifier aligned to the English subject, we may try to predict a corresponding AEP, which would likely involve the extended projection of a noun. Exactly how we would form the modifier AEPs (for instance for prepositional phrases) would be part of this work.

This approach is compelling for a couple of reasons:

- it facilitates the modeling of syntactic structure conditioned on the intended role (subject, object, etc) of the target-language modifier;
- it offers an AEP framework that is entirely self-contained, without reliance on a phrase-based system.

This system is quite different from the integrated syntax and factor based system and should therefore make a very interesting point of comparison.

A.3.5 Summary

The goal of this research is to integrate a system that makes explicit use of global syntactic information with one that is able to incorporate factors in a phrase-based framework. We aim to use the mutual strengths of each system to produce high-quality automatic translations. We intend to test our model using German/English and Spanish/English language pairs. In addition, we plan to implement several improvements to the AEP prediction model, as well some alternative end-to-end translation models that make use of the AEP model and can act as points of comparison to the integrated syntax and factor based model. We hope that this work will not only produce better machine translation output, but will also help elucidate how syntactic information can best be used for SMT.

Appendix B

Detailed Results for the Czech-English Experiments

This appendix goes into great detail about the Czech↔English translation experiments that were described in a summarized form in Section **??**.

Section B.1 describes the data used for our experiments, including preprocessing steps and some basic statistics. Section B.2 introduces the metric and lists some known result on MT quality on our dataset, including the scores of human translation. The core of this report is contained in Section B.3 where all our experiments and results are described in detail.

B.1 Data Used

B.1.1 Corpus Description and Preprocessing

The data used for Czech↔English experiments are available as CzEng 0.5 (Bojar and Žabokrtský [2006]) and PCEDT 1.0 (Čmejrek et al. [2004]). The collection contains parallel texts from various domains, as summarized in Table B.1.

	Sentences		Tokens	
	Czech	English	Czech	English
Texts from European Parliament	77.7%	71.7%	78.2%	75.9%
E-Books	5.5%	6.6%	7.2%	7.4%
KDE (open-source documentation)	6.9%	10.2%	2.6%	3.6%
PCEDT-WSJ (Wall Street Journal texts)	1.5%	1.7%	2.6%	2.8%
Reader's Digest stories	8.4%	9.7%	9.4%	10.3%
Total	1.4 M	1.3 M	19.0 M	21.6 M

Table B.1: Domains of texts contained in full training data.

The texts in CzEng are pre-tokenized and pre-segmented (sentence boundaries identified) and automatically sentence-aligned using the hunalign tool (Varga et al. [2005]). The PCEDT data are manually sentence aligned 1-1 by origin, because the Czech version of the text was obtained by translating English text sentence by sentence.

For the purposes of our experiments, we processed the data using the tools listed in Table B.2. The English side of the corpus had to be retokenized (keeping CzEng sentence boundaries), because the original tokenization was not compatible with the tagging tool.

	Czech	English
Segmentation	CzEng	CzEng
Tokenization	CzEng	Like Europarl, Koehn [2005]
Morph./POS Tagging	Hajič and Hladká [1998]	Ratnaparkhi [1996]
Lemmatization	Hajič and Hladká [1998]	-not used-
Parsing	McDonald et al. [2005]	-not used-

Table B.2: Czech and English tools used to annotate CzEng data.

Corpus		Sentences	Tokens
Baseline: PCEDT	Czech	20,581	453,050
	English	20,581	474,336
Large: CzEng+PCEDT	Czech	862,398	10,657,552
	English	862,398	12,001,772

Table B.3: Data sizes available for our experiments.

B.1.2 Baseline (PCEDT) and Large (CzEng+PCEDT) Corpus Data

The evaluation set of sentences used in our experiments (see section B.1.3 below) comes from the very specific domain of Wall Street Journal. The PCEDT-WSJ section matches this domain exactly, so we use the PCEDT-WSJ section (20k sentences) as the training data in most of our experiments and refer to it by the term "baseline corpus" or simply PCEDT. In some experiments, we make use of all the training data (860k sentences) and refer to it as the "large corpus". (Of course, test data are always excluded from training.)

Table B.3 reports exact data sizes of the baseline and large corpora used for our experiments. (Note that the baseline corpus is a subset of the large corpus.) The data size is significantly lower than what CzEng offers, because not all of the sentences successfully passed through all our tools and also due to the removal of sentences longer than 50 words and sentences with the ratio between Czech and English number of tokens worse than 9.

B.1.3 Tuning and Evaluation Data

Our tuning and evaluation data consist of 515 sentences with 4 reference translations. The dataset was first published as part of PCEDT 1.0 for evaluating Czech→English translation and included original English Wall Street Journal (WSJ) texts translated to Czech (sentence by sentence) and 4 independent back-translations to English. For the purposes of English→Czech translation in our experiments, another 4 independent translations from the original English to Czech were obtained.

For our experiments we kept the original division of the dataset into two parts: the tuning (development) set and the evaluation test set. However, we retokenized all the sentences with the Europarl tokenization tool. Dataset sizes in terms of number of sentences, input tokens and input tokens never seen in the PCEDT training corpus (out-of-vocabulary, OOV) are listed in Table B.4.

We followed the common procedure to use tuning dataset to set parameters of the translation system and to use the evaluation dataset for final translation quality estimate. In other words, the translation system has access to the reference translations of the tuning dataset but never has access to the reference translations of the evaluation dataset.

In the following, we use the this short notation: "Dev (std)" denotes results obtained on the tuning dataset with the model parameters set to the default, somewhat even distribution. "Dev

		Input Tokens When Translating from			
	Sentences	Czech	OOV	English	OOV
Tuning	259	6429	6.8%	6675	3.5%
Evaluation	256	5980	6.9%	6273	3.8%

Table B.4: Tuning and evaluation data.

(opt)” denotes results on the tuning dataset with the parameters optimized using minimum error rate training procedure (see section 6.4). The “Dev (opt)” results are always overly optimistic, because MERT had access to the reference translations and tunes the MT output to get the highest scores possible. “Test (opt)” denotes results on evaluation set with model parameters as optimized on the tuning set. The “Test (opt)” results thus estimate the system performance on unseen data and allow for a fair comparison.

For the purposes of automatic translation, the input texts were analyzed using the same tools as listed in section B.1.1.

B.2 MT Quality Metric and Known Baselines

Throughout all our experiments, we use the BLEU metric (Papineni et al. [2002]) to automatically assess the quality of translation. We use an implementation of this metric provided for the workshop. Other implementations such as IBM original or NIST official `mt_eval` might give slightly different absolute results, mainly due to different tokenization rules.

In all experiments reported below, we train and test the system in *case-insensitive* fashion (all data are converted to lowercase, including the reference translations), except where stated otherwise.

B.2.1 Human Cross-Evaluation

Table B.5 displays the scores if we evaluate one human translation against 4 other human translations. For the sake of completeness, we report not only the default lowercase (LC) evaluation but also case sensitive (CSens) evaluation. This estimate cannot be understood as any kind of a bound or limit on MT output scores, but it nevertheless gives some vague orientation when reading BLEU figures.

			To Czech			To English	
		Min	Average	Max	Min	Average	Max
Evaluation	LC	38.5	43.1±4.0	48.4	41.6	54.5±8.4	62.9
	CSens	38.1	42.5±4.0	47.8	41.1	53.8±8.4	62.4
Tuning	LC	39.0	46.3±4.3	49.3	45.8	55.3±6.0	61.7
	CSens	38.3	45.8±4.4	48.8	45.0	54.7±6.1	61.3

Table B.5: BLEU scores of human translation against 4 different human translations. Evaluated 5 times, always comparing one translation against the 4 remaining. The minimum, average and maximum scores of the 5-fold estimation are given.

As expected, we observe a higher variance (standard deviation) when evaluating translation to English. The reason is that one of the five English versions of the sentences is the original, while the other four were back translated from Czech. It is therefore quite likely for the four back translations to differ more from the original than from each other raising the BLEU variance.

English scores are generally higher and this may indicate that there is less variance in word order, lexical selection or word morphology in English, but it also could be the simple case that the translators to English produced more rigid translations.

B.2.2 BLEU When not Translating at All

Our particular type of text (WSJ) contains a lot of numbers and proper names that are often not altered during translation. Just for curiosity and to check that our datasets are not just numbers, punctuation and company names, we evaluate BLEU for texts not translated at all. I.e. the input text is evaluated against the standard 4 references. As displayed in Table B.6, the scores are very low but nonzero, as expected.

		To Czech	To English
Evaluation	Lowercase	2.20	2.66
Evaluation	Case Sensitive	2.20	2.65
Tuning	Lowercase	2.93	3.60
Tuning	Case Sensitive	2.93	3.59

Table B.6: BLEU scores when not translating at all, i.e. only punctuation, numbers and some proper names score.

B.2.3 Previous Research Results

Table B.7 summarizes previously published results of Czech→English translation. Dependency-based MT (DBMT, Čmejrek et al. [2003]) is a system with rule-based transfer from Czech deep syntactic trees (obtained automatically using one of two parsers of Czech) to English syntactic trees. GIZA++ (Och and Ney [2003]) and ReWrite (Germann [2003]) is the "standard baseline" word-based statistical system. PBT (Zens et al. [2005]) is a phrase-based statistical MT system developed at RWTH Aachen that has been evaluated on English-Czech data by Bojar et al. [2006].

	Average over 5 refs.		4 refs. only	
	Dev	Test	Dev	Test
DBMT with parser I, no LM	18.57	16.34	-	-
DBMT with parser II, no LM	19.16	17.05	-	-
GIZA++ & ReWrite, bigger LM	22.22	20.17	-	-
PBT, no additional LM	38.7±1.5	34.8±1.3	36.3	32.5
PBT, bigger LM	41.3±1.2	36.4±1.3	39.7	34.2
PBT, more parallel texts, bigger LM	42.3±1.1	38.1±0.8	41.0	36.8

Table B.7: Previously published results of Czech→English MT.

All figures in Table B.7 are based on the same training dataset as we use: the baseline corpus of PCEDT (20k sentences) and on the same tuning and evaluation sets. However, the tokenization of the data is slightly different the we use and also a different implementation of the BLEU metric was used. Our experience is that a different scoring script can change BLEU results by about 2 points absolute, so these numbers should not be directly compared to our results reported here.

Unlike Čmejrek et al. [2003] who evaluate four-reference BLEU five times using the original English text in addition to the 4 available reference back-translations in a leave-one out procedure, we always report BLEU estimated on the 4 reference translations only.

To the best of our knowledge, we are the first to evaluate English→Czech machine translation quality with automatic measures.

B.3 Experiments

B.3.1 Motivation: Margin for Improving Morphology

Czech is a Slavonic language with very rich morphology and relatively free word order. (See e.g. Bojar [2004] for more details.) The Czech morphological system defines 4,000 tags in theory and 2,000 were actually seen in a big tagged corpus. (For comparison, the English Penn Treebank tagset contains just about 50 tags.) When translating to Czech, any MT system has to face the richness and generate output words in appropriate forms.

Table B.8 displays BLEU scores of single-factored translation English→Czech using the baseline corpus only. The second line in the table gives the scores if morphological information was disregarded in the evaluation: the MT output is lemmatized (word forms replaced with their respective base forms) and evaluated against lemmatized references.

	Dev (std)	Dev (opt)	Test (opt)
Regular BLEU, lowercase	25.68	29.24	25.23
Lemmatized MT output against lemmatized references	34.29	38.01	33.63

Table B.8: Margin in BLEU for improving morphology.

We see that more than 8 point BLEU absolute could be achieved if output word forms were chosen correctly.[1] This observation gives us a strong motivation for focussing on morphological errors first.

B.3.2 Obtaining Reliable Word Alignment

Given the richness of Czech morphological system and quite limited amount of data in the baseline corpus (20k sentences), our first concern was to obtain reliable word alignments. Like Bojar et al. [2006], we reduce the data sparseness by either lemmatizing or stemming Czech tokens and stemming English tokens. (By stemming we mean truncating each word to at most 4 characters.) The vocabulary size of Czech word forms reduces to a half after stemming or lemmatization and comes thus very close to the vocabulary size of English word forms.

Table B.9 displays BLEU scores on Test (opt) English→Czech depending on the preprocessing of corpus for word alignment. The translation process itself was performed on full word forms (single-factored), with a single trigram language model collected from the Czech side of the parallel corpus. In all cases, we employed the grow-diag-final heuristic for symmetrization of two independent GIZA++ runs.

The results confirm improvement in translation quality if we address the data sparseness problem for alignments either by full lemmatization or by simple stemming. Surprisingly, using full lemmatization of the Czech side scored worse than just stemming Czech. This result

[1] Although not all required word forms may be available in the training data, we could easily generate output word forms from lemmas and morphological tags deterministically using a large target-side-only dictionary.

Preprocessing for Alignment		Parallel Corpus Used	
English	Czech	Baseline (20k sents.)	Large (860k sents.)
word forms	word forms	25.17	-
4-char stems	lemmas	25.23	25.40
4-char stems	4-char stems	25.82	24.99

Table B.9: BLEU in English→Czech translation depending on corpus preprocessing for word alignment.

was confirmed neither on the large training set, nor by Bojar et al. [2006] for Czech→English direction, so we attribute this effect to random fluctuations in MERT procedure.

We also see nearly no gain or even some loss by increasing the corpus size from 20k to 860k sentences. (See section B.3.5 below for more details on various ways of using more data.) This observation can be explained by the very specific domain of our test set.

B.3.3 Scenarios of Factored Translation English→Czech

Scenarios Used

We experimented with the following factored translation scenarios:

The baseline scenario is single-factored: input (English) lowercase word forms are directly translated to target (Czech) lowercase forms. A 3-gram language model (or more models based on various corpora) checks the stream of output word forms.

We call this the "T" (translation) scenario.

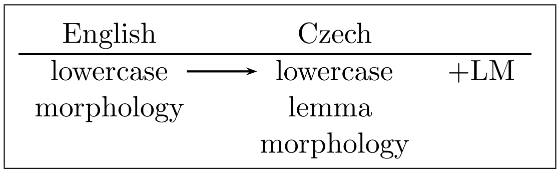


Figure B.1: Single-factored scenario (T).

In order to check the output not only for word-level coherence but also for morphological coherence, we add a single generation step: input word forms are first translated to output word forms and each output word form then generates its morphological tag.

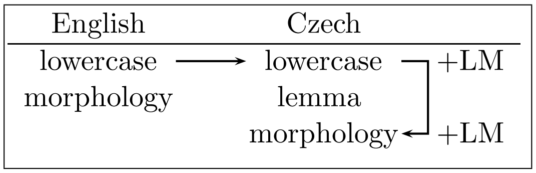


Figure B.2: Checking morphology (T+C).

Two types of language models can be used simultaneously: a (3-gram) LM over word forms and a LM over morphological tags. For the morphological tags, a higher-order LM can be used, such as 7 or 9-gram.

We used tags with various levels of detail, see section B.3.4. We call this the "T+C" (translate and check) scenario.

As a refinement of T+C, we also used T+T+C scenario, where the morphological output stream is constructed based on both, output word forms and input morphology. This setting should ensure correct translation of morphological features such as number of source noun phrases.

Again, two types of language models can be used in this "T+T+C" scenario.

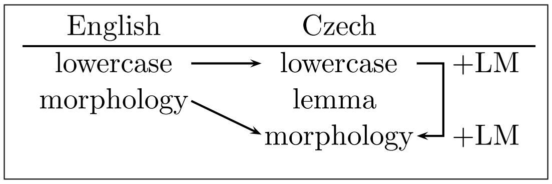


Figure B.3: Translating and checking morphology (T+T+C).

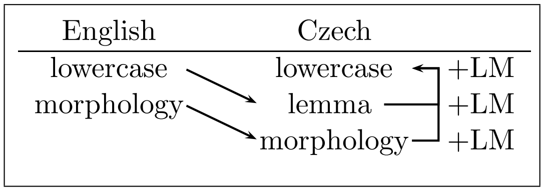


Figure B.4: Generating forms from lemmas and tags (T+T+G).

The most complex scenario we used is linguistically appealing: output lemmas (base forms) and morphological tags are generated from input in two independent translation steps and combined in a single generation step to produce output word forms. The input English text was not lemmatized so we used English word forms as the source for producing Czech lemmas.

The "T+T+G" setting allows us to use up to three types of language models. Trigram models are used for word forms and lemmas and 7 or 9-gram language models are used over tags.

Experimental Results: T+C Works Best

Table B.10 summarizes estimated translation quality of the various scenarios. In all experiments, only the baseline corpus of 20k sentences was used with word alignment obtained using grow-diag-final heuristic on stemmed English and lemmatized Czech input streams. Language models are also based on the 20k sentences only, 3-grams are used for word forms and lemmas, 7-grams for morphological tags.

	Dev (std)	Dev (opt)	Test (opt)
Baseline: T	25.68	29.24	25.23
T+T+G	23.93	30.34	25.94
T+T+C	25.12	30.73	26.43
T+C	23.51	**30.88**	**27.23**

Table B.10: BLEU scores of various translation scenarios.

The good news is that multi-factored models always outperform the baseline T (except for "Dev (std)", but this is not surprising, as the default weights can be quite bad for multi-factored translation).

Unfortunately, the more complex a multi-factored scenario is, the worse the results are. Our belief is that this effect is caused by search errors: with multi-factored models, more hypotheses get similar scores and future costs of partial hypotheses might be estimated less reliably. With the limited stack size (not more than 200 hypotheses of the same number of covered input words), the decoder may more often find sub-optimal solutions.

To conclude, the scenario for just checking output morphology (T+C) gives us the best results, 27.23 BLEU, 2 points absolute improvement over the single-factored baseline.

B.3.4 Granularity of Czech Part-of-Speech

As stated above, Czech morphological tag system is very complex, in theory up to 4,000 different tags are possible. In our T+C scenario, we experiment with various simplifications of the system to find the best balance between expresivity and richness of the statistics available in our corpus. (The more information is retained in the tags, the more severe data sparseness is.)

Full tags (1098 unique seen in baseline corpus): Full Czech positional tags are used. A tag consists of 15 positions, each holding the value of a morphological property (e.g. number, case or gender).

POS (173 unique seen): We simplify the tag to include only part and subpart of speech (distinguishes also partially e.g. verb tenses). For nouns, pronouns, adjectives and prepositions[2], also the case is included.

CNG01 (571 unique seen): CNG01 refines POS. For nouns, pronouns and adjectives we include not only the case but also number and gender.

CNG02 (707 unique seen): Tag for punctuation is refined: lemma of the punctuation symbol is taken into account; previous models disregarded e.g. the distributional differences between a comma and a question mark. Case, number and gender added to nouns, pronouns, adjectives, prepositions, but also to verbs and numerals (where applicable).

CNG03 (899 unique seen): Highly optimized tagset:

- Tags for nouns, adjectives, pronouns and numerals describe the case, number and gender; the Czech reflexive pronoun *se* or *si* is highlighted by a special flag.
- Tag for verbs describes subpart of speech, number, gender, tense and aspect; the tag includes a special flag if the verb was the auxiliary verb *být (to be)* in any of its forms.
- Tag for prepositions includes the case and also the lemma of the preposition.
- Lemma included for punctuation, particles and interjections.
- Tag for numbers describes the "shape" of the number (all digits are replaced by the digit *5* but number-internal punctuation is kept intact). The tag thus distinguishes between 4- or 5-digit numbers or the precision of floating point numbers.
- Part of speech and subpart of speech for all other words.

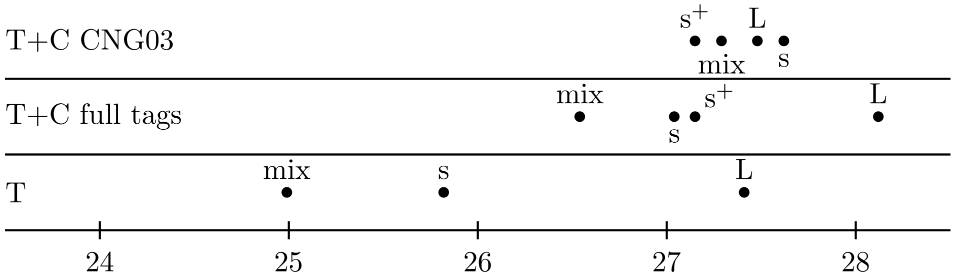
Experimental Results: CNG03 Best

Table B.11 summarizes the results of T+C scenario with varying detail in morphological tag. All the results were obtained using only the baseline corpus of 20k sentences, word-alignment symmetrized with grow-diag-final heuristic and based on stemmed Czech and English input. Also the language models are based solely on the 20k sentences. Trigrams are used for word forms and 7-grams for tags.

	Dev (std)	Dev (opt)	Test (opt)
Baseline: T (single-factor)	26.52	28.77	25.82
T+C, CNG01	22.30	29.86	26.14
T+C, POS	21.77	30.27	26.57
T+C, full tags	22.56	29.65	27.04
T+C, CNG02	23.17	**30.77**	27.45
T+C, CNG03	23.27	30.75	**27.62**

Table B.11: BLEU scores of various granularities of morphological tags in T+C scenario.

Our results confirm significant improvement over single-factored baseline. Detailed knowledge of the morphological systems also proves its utility: by choosing the most relevant features of tags and lemmas but avoiding sparseness, we can improve about 0.5 BLEU absolute over T+C with full tags. Too strict reduction of features used causes a loss.



s	small data, 20k sentences in the domain
s$^+$	small data, 20k sentences in the domain with an additional separate LM (860k sents out of the domain)
L	large data, 860k sentences, separate in-domain and out-of-domain LMs
mix	large data, 860k sentences, a single LM mixes the domains

Scenario	Acronym	Parallel Corpus	Language Models	Dev (std)	Dev (opt)	Test (opt)
T	mix	Large (860k)	Large (860k)	23.47	28.74	24.99
T	s	Baseline (20k)	Baseline (20k)	26.52	28.77	25.82
T+C full tags	mix	Large (860k)	Large (860k)	15.66	29.50	26.54
T+C full tags	s	Baseline (20k)	Baseline (20k)	22.56	29.65	27.04
T+C full tags	s$^+$	Baseline (20k)	20k+860k	19.97	30.33	27.15
T+C CNG03	s$^+$	Baseline (20k)	20k+860k	19.95	30.48	27.15
T+C CNG03	mix	Large (860k)	Large (860k)	15.77	30.71	27.29
T	L	Large (860k)	20k+860k	19.45	29.42	27.41
T+C CNG03	L	Large (860k)	20k+860k	14.22	30.33	27.48
T+C CNG03	s	Baseline (20k)	Baseline (20k)	23.27	30.75	27.62
T+C full tags	L	Large (860k)	20k+860k	14.06	30.64	**28.12**

Figure B.5: The effect of additional data in T and T+C scenarios.

B.3.5 More Out-of-Domain Data in T and T+C Scenarios

Figure B.5 gives a chart and full details on our experiments with adding more data into the T and T+C scenarios. We varied the scenario (T or T+C), the level of detail in the T+C scenario (full tags vs. CNG03), the size of the parallel corpus used to extract phrases (Baseline vs. Large, as described in section B.1.2) and the size or combination of target side language models (a single LM based on the Baseline or Large corpus, or both of them with separate weights set in the MERT training).

Several observations can be made:

- Ignoring the domain difference and using only the single Large language model (denoted “mix” in the chart) hurts. Only the “T+C CNG03” scenario does not confirm this observation and we believe this can be attributed to some randomness in MERT training of “T+C CNG03 s$^+$”.

- CNG03 outperforms full tags only in small data setting, with large data (treating the domain difference properly), full tags are significantly better.

- The improvement of T+C over T decreases if we use more data.

[2] Some Czech prepositions select for a particular case, some are ambiguous. Although the case is never shown on surface of the preposition, the tagset includes this information and Czech taggers are able to infer the case.

An adjective in MT output...	Portion
agrees with the governing noun	**74%**
depends on a verb (cannot check the agreement)	7%
misses the governing noun (cannot check the agreement)	7%
should not occur in MT output	5%
has the governing noun not translated (cannot check the agreement)	5%
mismatches with the governing noun	**2%**

Table B.12: Microstudy: adjectives in English→Czech MT output.

Translation of	Verb	Modifier
...preserves meaning	56%	79%
...is disrupted	14%	12%
...is missing	27%	1%
...is unknown (not translated)	0%	5%

Table B.13: Analysis of 77 Verb-Modifier pairs in 15 sample sentences.

B.3.6 First Experiments with Verb Frames

Microstudy: Current MT Errors

The previous sections described significant improvements gained on small data sets when checking morphological agreement or adding more data (BLEU raised from 25.82% to 27.62% or up to 28.12% with additional out-of-domain parallel data). However, the best result achieved is still far below the margin of lemmatized BLEU, as estimated in section B.3.1. In fact, lemmatized BLEU of our best result is yet a bit higher (35%), indicating that T+C improve not only morphology, but also word order or lexical selection issues.

We performed a microstudy on local agreement between adjectives and their governing nouns. Altogether 74% of adjectives agreed with the governing noun and only 2% of adjectives did not agree; the full listing is given in Table B.12.

Local agreement thus seems to be relatively correct. In order to find the source of the remaining morphological errors, we performed another microstudy of current best MT output (BLEU 28.12%) using an intuitive metric. We checked whether Verb-Modifier relations are properly preserved during the translation of 15 sample sentences.

The *source* text of the sample sentences contained 77 Verb-Modifier pairs. Table B.13 lists our observations on the two members in each Verb-Modifier pair. We see that only 43% of verbs are translated correctly and 79% of nouns are translated correctly. The system tends to skip verbs quite often (21% of cases).

More importantly, our analysis has shown that even in cases where both the Verb and the Modifier are correct, the relation between them in Czech is either non-gramatical or meaning-disturbing in 56% of these cases. Commented samples of such errors are given in Figure B.6. The first sample shows that a strong language model can lead to the choice of a grammatical relation that nevertheless does not convey the original meaning. The second sample illustrates a situation where two correct options are available but the system chooses an inappropriate relation, most probably because of backing off to a generic pattern verb-noun$_{plural}^{accusative}$. This pattern is quite common for for expressing the object role of many verbs (such as *vydat*, see Correct option 2 in Figure B.6), but does not fit well with the verb *vyběhnout*. While the target-side data may be rich enough to learn the generalization vyběhnout–s–*instr*, no such generalization is possible with language models over word forms or morphological tags only. The target side data

Input:	Keep on investing.
MT output:	Pokračovalo investování. (grammar correct here!)
Gloss:	Continued investing. (Meaning: The investing continued.)
Correct:	Pokračujte v investování.

Input:	brokerage firms rushed out ads . . .			
MT Output:	brokerské	firmy	vyběhl	reklamy
Gloss:	brokerage	firms$_{pl.fem}$	ran$_{sg.masc}$	ads$^{pl.voc,sg.gen}_{pl.nom,pl.acc}$
Correct option 1:	brokerské	firmy	vyběhly	s reklamami$_{pl.instr}$
Correct option 2:	brokerské	firmy	vydaly	reklamy$_{pl.acc}$

Figure B.6: Two sample errors in translating Verb-Modifier relation from English to Czech.

will be hardly ever rich enough to learn this particular structure in all correct morphological and lexical variants: *vyběhl–s–reklamou, vyběhla–s–reklamami, vyběhl–s–prohlášením, vyběhli–s–oznámením, . . .* . We would need a mixed model that combines verb lemmas, prepositions and case information to properly capture the relations.

To sum up, the analysis has revealed that in our best MT output:

- noun-adjective agreement is already quite fine,
- verbs are often missing,
- verb-modifier relations are often malformed.

Design of Verb Frame Factor

In this section we describe a model that combines verb lemmas, prepositions and noun cases to improve the verb-modifier relations on the target side and possibly to favour keeping verbs in MT output. The model is incorporated to our MT system in the most simple fashion: we simply create an additional output factor to explicitly model target verb valency/subcategorization, i.e. to mark verbs and their modifiers in the output. An independent language model is used to ensure coherence in the verb frame factor.

Figure B.7 illustrates the process of converting a Czech sentence to the corresponding verb frame factor. We make use of the dependency analysis of the sentence and associate each input word with a token:

- tokens for verbs have the form *H:V⟨subpart of speech⟩:⟨verb lemma⟩* indicating that the verb is the head of the frame,
- tokens for words depending on a verb have the form *M:⟨slot description⟩* to denote verb frame members. Slot description is based on the respective modifier:
  - slot description for nouns, pronouns and (nominalized) adjectives contains only the case information (e.g. *subst*$_{nom}$ for nouns or pronouns in nominative),
  - slot description for prepositions contains the preposition lemma and the case (e.g. *prep:na*$_{acc}$ for the preposition *na* in accusative),
  - sub-ordinating conjunctions are represented by their lemma (e.g. *subord:zda* for the conjunction *zda*),
  - co-ordinating conjunctions are treated in an oversimplified manner, the slot description just notes that there was a co-ordinating conjunction. No information is propagated from the co-ordinated elements.

  - adverbs are completely ignored, i.e. get a dummy token —

- punctuation symbols have the form *PUNCT:⟨punctuation symbol⟩* and conjunctions have the form *DELIM:⟨subpart of speech⟩:⟨conjunction lemma⟩* to keep track of structural delimiters in the verb frame factor,
- all other words get a dummy token —.

Thus for the beginning of the sample sentence in Figure B.7 *Poptávka trvale stoupá za podpory. . . (The demand has been consistently growing under the encouragement. . .)* we create the following stream:

$$\text{M:subst}_{nom} \text{ — H:VB:stoupat M:prep:za}_{gen} \text{ —}$$

The stream indicates that the verb *stoupat* tends to be modified by a (preceding) subject and (following) argument or adjunct governed by the preposition *za* in genitive.

Keeping in mind the valency theory for Czech (e.g. Panevová [1994]), there are several limitations in our model:

- We do not make any distinctions between argument and adjuncts (except for the above mentioned deletion of adverbs). Ideally, all adjuncts would get the dummy token —.
- In theory, the order of verb frame members is not grammatically significant for some languages, so we should allow independent reordering of the verb frame factor.
- If a verb depends on a verb, their modifiers can be nearly arbitrarily mixed within the clause (in Czech). Our model does not distinguish which modifiers belong to which of the verbs.

Another problem with the verb frame factor is the explicit representation of the number of intervening words (tokens —). A skipping language model would be necessary to describe the linguistic reality more adequately.

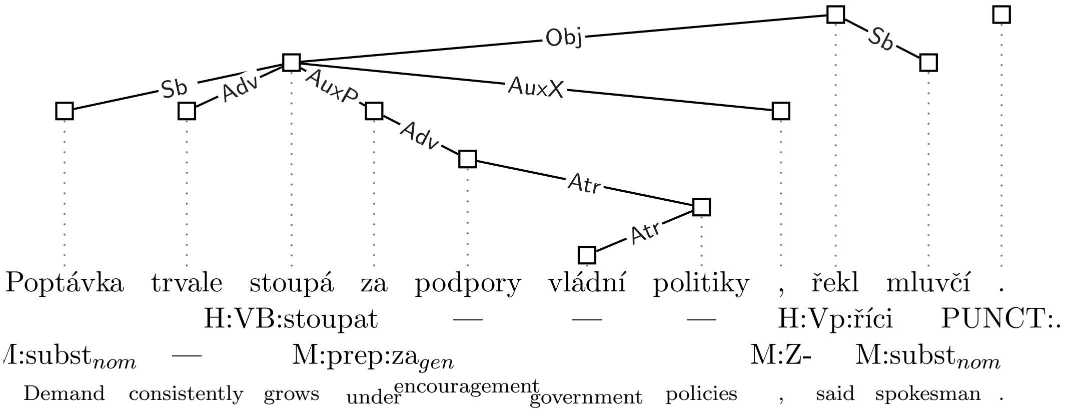

Obj
Sb
Sb
Adv
AuxP
AuxX
Adv
Atr
Atr
Poptávka trvale stoupá za podpory vládní politiky , řekl mluvčí .
H:VB:stoupat — — — H:Vp:říci PUNCT:.
/I:subst_nom — M:prep:za_gen M:Z- M:subst_nom
Demand consistently grows under encouragement government policies , said spokesman .

Figure B.7: Verb frame factor based on dependency syntax tree of a sample sentence: *Demand has been growing consistently under the encouragement of government policies, a spokesman said.*

Preliminary Results with Verb Frame Factor

Table B.14 displays BLEU scores of the scenario translate-and-check verb factor (T+Cvf) compared to the single-factored baseline (T). Word alignment for these experiments was obtained using grow-diag-final heuristic on stemmed English and lemmatized Czech texts. Only the baseline corpus (20k sentences) was used to extract phrase tables. The verb frame factor language model is a simple n-gram LM with n of 7, 9 or 11 and it is based either on the baseline corpus (PCEDT) or the Czech side of the Large corpus. In all cases, a simple trigram model checks the fluency of word form stream.

	Dev (std)	Dev (opt)	Test (opt)
T+Cvf LM-11gr-Large	19.51	28.68	24.23
T+Cvf LM-7gr-Baseline	19.75	28.54	25.05
T+Cvf LM-7gr-Large	19.69	28.32	25.07
T+Cvf LM-9gr-Large	19.55	27.98	25.09
Baseline: T	25.68	29.24	**25.23**

Table B.14: Preliminary results with checking of verb frame factor.

Unfortunately, all T+Cvf results fall below the single-factored baseline. Table B.15 gives some more detail on this result. We performed the same type of analysis of verb-modifier pairs in the first 15 output sentences, as described in section B.3.6. The baseline columns are based on the single-factored output (BLEU 25.23), the VFF columns are based on T+Cvf LM-11gr-Large (BLEU 24.23).

Translation of	**Verb**		**Modifier**	
	Baseline	VFF	Baseline	VFF
. . . preserves meaning	38	40	57	55
. . . is disrupted	17	20	15	15
. . . is missing	15	10	0	1
. . . is unknown (not translated)	7	7	5	6

Table B.15: Analysis of 77 Verb-Modifier pairs in baseline output and in verb-frame-factor (VFF) output.

Despite the very small size of our sample, some effects of adding the verb-frame-factor can be observed. On the positive side, verbs are not missing in MT output that often. On the negative side, translation of verbs or nouns gets confused by the additional factor. Unfortunately, also the percentage of correctly translated verb-modifier relations in cases where both verb and modifier are fine decreased.

Unless the experiment is repeated with more training data and also with a larger set of evaluated sentences, it is hard to make any conclusions. The verb frame factor at least leads to some more verbs in MT output.

B.3.7 Single-factored Results Czech→English

Our primary interest was in English→Czech translation but we also experimented with Czech→English direction, mainly to allow for comparison with previous reported results.

It should be noted that translating to English in our setting is easier. In general, there are fewer word forms in English so language models face milder data spareness and there are fewer chances to make an error (BLEU would notice). Moreover, the particular test set we use contains input Czech text that came from an English original and was translated sentence by sentence. The Czech thus probably does not exhibit full richness and complexity of word order and language constructions and is easier to translate back to English than a generic Czech text would be.

Scenario	Parallel Corpus	Language Models	Dev (std)	Dev (opt)	Test (opt)
T	Baseline (20k)	Baseline (20k)	28.97	35.39	28.50
T+C	Baseline (20k)	Baseline (20k)	23.07	36.13	28.66
T	Large (860k)	20k+860k	19.31	39.60	33.37
T	Large (860k)	Large (860k, i.e. mix)	28.94	40.15	**34.12**

Table B.16: Sample Czech→English BLEU scores.

Table B.16 lists Moses results of Czech→English translation. We observe a minor improvement when checking the part-of-speech factor (T+C). A larger improvement is obtained by adding more data and quite differently from English→Czech results (see section B.3.5), mixing in-domain and out-of-domain LM data does not hurt the performance.

B.3.8 Summary and Conclusion

We experimented with factored English→Czech translation. The majority of our experiments were carried out in a small data setting and we translated to a morphologically rich language. In this setting, lemmatization or stemming of training data is vital for obtaining reliable alignments. Multi-factored translation for ensuring coherence of morphological properties of output words significantly increases BLEU performance, although the effect is reduced with additional training data. Experiments also indicate that more complex translation scenarios lower the scores, probably due to more severe search errors.

Our English→Czech experiments confirm that in minimum-error-rate training, it is helpful to keep language models based on in- and out-of-domain data separate. We did not observe this domain sensitivity in Czech→English direction.

Based on manual analysis of sample output sentences, we also conducted some preliminary experiments on using target-side syntactic information in order to improve grammaticality of verb-modifier relations. The results are rather inconclusive and further refinement of the model would be necessary.

Appendix C

Undergraduate Projects

This appendix details the work undertaken by the three exceptional undergraduates who participated in the summer workshop. Their projects focused on three different topics:

- Alexandra Constantin's project focused on extending factored translation models to be used in the *word alignment* phrase of translation, rather than in the *decoding* phrase which was the general thrust of the workshop. Her project is described in Section C.1.
- Christine Corbett Moran collaborated with Brooke Cowan to implement lexicalized reordering models in Moses. This was one of the single largest improvements to overall translation quality which was incorporated during the workshop. It is described in Section C.2.
- Evan Herbst created a set of tools for performing error analysis of machine translation output. His project provided visualization tools for the translations of individual sentences, as well as a set of tools for summary statistics at the corpus level. His project described in Section C.3.

C.1 Linguistic Information for Word Alignment

C.1.1 Word Alignment

If we open a common bilingual dictionary, we find that many words have multiple translations, some of which are more likely than others, for instance:

Haus = house, building, home, household

If we had a large collection of German text, paired with its translation into English, we could count how often $Haus$ is translated into each of the given choices. We can use the counts to estimate a lexical translation probability distribution

$$t : e|f \rightarrow t(e|f)$$

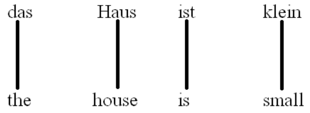
that, given a foreign word, f, returns a probability for each choice for an English translation e, that indicates how likely that translation is.

We can derive an estimate of the translation probability distribution from the data by using the ratio of the counts. For example, if we have 10000 occurrences of $Haus$ and 8000 translate to *house*, then $t(house|Haus) = 0.8$.

For some words that are infrequent in the corpus, the estimates of the probability distribution are not very accurate. Using other linguistic information, such as observing that in a specific language pair verbs usually get translated as verbs, could help in building a more accurate translation.

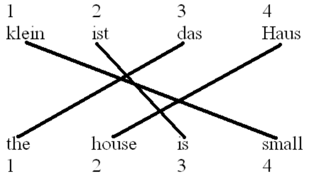
Let's look at an example. Imagine we wanted to translate the German sentence *das Haus ist klein*. The sentence can be translated word by word into English. One possible translation is *the house is small*.

Implicit in these translations is an alignment, a mapping from German words to English words:



An alignment can be formalized with an alignment function $a : i \rightarrow j$. This function maps each English target word at position i to a German source word at position j.

For example, if we are given the following pair of sentences:



the alignment function will be $a : \{1 \rightarrow 3, 2 \rightarrow 4, 3 \rightarrow 2, 4 \rightarrow 1\}$.

C.1.2 IBM Model 1

Lexical translations and the notion of alignment allow us to define a model capable of generating a number of different translations for a sentence, each with a different probability. One such model is IBM Model 1, which will be described below.

For each target word e that is produced by the model from a source word f, we want to factor in the translation probability $t(e|f)$.

The translation probability of a foreign sentence $\mathbf{f} = (f_1, \ldots, f_{l_f})$ of length l_f into an English sentence $\mathbf{e} = (e_1, \ldots, e_{l_e})$ of length l_e with an alignment of each English word e_j to a foreign word f_i according to alignment $a : j \rightarrow i$ is:

$$p(\mathbf{e}, a|\mathbf{f}) = \frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})$$

C.1.3 Learning the Lexical Translation Model

A method for estimating these translation probability distributions from sentence-aligned parallel text is now needed.

The previous section describes a strategy for estimating the lexical translation probability distributions from a word-aligned parallel corpus. However, while large amounts of sentence-aligned parallel texts can be easily collected, word-aligned data cannot. We would thus like to estimate these lexical translation distributions without knowing the actual word alignment, which we consider a hidden variable. To do this, we use the Expectation-Maximization algorithm:

- Initialize model (typically with uniform distribution)
- Apply the model to the data (expectation step)
- Learn the model from the data (maximization step)

- Iterate steps 2-3 until convergence

First, we initialize the model. Without prior knowledge, uniform probability distributions are a good starting point. In the expectation step, we apply the model to the data and estimate the most likely alignments. In the maximization step, we learn the model from the data and augment the data with guesses for the gaps.

Expectation step

When we apply the model to the data, we need to compute the probability of different alignments given a sentence pair in the data:

$$p(a|\mathbf{e},\mathbf{f}) = \frac{p(\mathbf{e},a|\mathbf{f})}{p(\mathbf{e}|\mathbf{f})}$$

$p(\mathbf{e}|\mathbf{f})$, the probability of translating sentence $\mathbf{f}$ into sentence $\mathbf{e}$ is derived as:

$$p(\mathbf{e}|\mathbf{f}) = \sum_a p(\mathbf{e},a|\mathbf{f}) = \prod_{j=1}^{l_e} \sum_{i=0}^{l_f} t(e_j|f_i)$$

Putting the previous two equations together,

$$p(a|\mathbf{e},\mathbf{f}) = \frac{p(\mathbf{e},a|\mathbf{f})}{p(\mathbf{e}|\mathbf{f})} = \prod_{j=1}^{l_e} \frac{t(e_j|f_{a(j)})}{\sum_{i=0}^{l_f} t(e_j|f_i)}.$$

Maximization Step

For the maximization step, we need to collect counts over all possible alignments, weighted by their probabilities. For this purpose, we define a count function c that collects evidence from a sentence pair $(\mathbf{e},\mathbf{f})$ that a particular source word f translates into a particular target word e.

$$c(e|f;\mathbf{e},\mathbf{f}) = \sum_a p(a|\mathbf{e},\mathbf{f}) = \frac{t(e|f)}{\sum_{j=1}^{l_e} t(e|f_{a(j)})} \sum_{j=1}^{l_e} \delta(e,e_j) \sum_{i=0}^{l_f} \delta(f,f_i)$$

where $\delta(x,y)$ is 1 is $x=y$ and 0 otherwise.

Given the count function, we can estimate the new translation probability distribution by:

$$t(e|f;\mathbf{e},\mathbf{f}) = \frac{\sum_{(\mathbf{e},\mathbf{f})} c(e|f;\mathbf{e},\mathbf{f})}{\sum_f \sum_{(\mathbf{e},\mathbf{f})} c(e|f;\mathbf{e},\mathbf{f})}.$$

C.1.4 Introducing Part of Speech Information to the Model

In order to introduce part of speech information to the model, we need to consider the probability of translating a foreign word f_{word} with part of speech f_{POS} into English word e_{word} with part of speech e_{POS}. In order words, we need to consider the translation probability distribution $t(e|f)$, where e and f are vectors, $e = (e_{word}, e_{POS})$, $f = (f_{word}, f_{POS})$. In order to estimate this density function, we need to make some independence assumptions. Depending on the independence assumption, several models can be formed:

POS Model 1 Assuming that words are independent from their parts of speech, we can estimate the translation density as:

$$t(e|f) = t(e_{word}|f_{word}) * t(e_{POS}|f_{POS})$$

POS Model 2 Making weaker independence assumption, the translation density can be estimated as:

$$t(e|f) = \lambda p(e_{POS}|e_{word}) t(e_{word}|f_{word}) + (1-\lambda) p(e_{word}|e_{POS}) t(e_{POS}|f_{POS})$$

This model has the advantage that it can weigh the importance given to part-of-speech information.

C.1.5 Experiment

To test whether part-of-speech information improves alignment quality, we compared alignments generated using IBM Model 1, alignments generated using only part-of-speech information, and alignments generated using POS Model 1 against manual alignments. The metric used to compare the alignments was AER (alignment error rate). The data consisted of European Parliament German and English parallel corpora. Experiments were done using different sizes of corpora. The scores are presented in the following table:

AER	*10k*	*20k*	*40k*	*60k*	*80k*	*100k*
IBM Model 1	54.7	51.8	49.3	48.6	47.5	47.1
POS Only	76.0	75.4	75.5	75.1	75.3	75.1
POS Model 1	53.6	51.5	49.6	48.4	47.7	47.3

The first row indicates the number of sentences used for training and the first column indicates the model used to generate alignments.

As expected, the AER of the alignments generated using only part of speech information are very high, indicating that part-of-speech information is not sufficient to generate good alignments. However, an AER of around .75 indicates that there is some information provided by part-of-speech information that could be useful.

The AER of alignments generated with IBM Model 1 doesn't statistically differ from the AER of alignments generated with the additional part of speech information. One reason for this might be that the part-of-speech probability was given equal weight to the word probability, even though the latter is more important. POS Model 2 might thus generate an improvement in AER.

C.2 Distortion Models

Distortion modeling is used as a feature function in our translation system adding in a score based on the likely placement of a phrase relative to an adjacent phrase. Two main forms of distortion modeling are used in contemporary state-of-the-art machine translation systems: distance distortion models, which penalize based on the distance of the reorder, and lexical distortion models, which take into account the relationship between the phrase being reordered and adjacent phrases. Moses extends lexical distortion models to factor distortion models, models in which lexical distortion serves as the special case using the surface forms as the factors in the probability distribution table.

C.2.1 Distance Distortion Models

Distance based distortion models consider the number of words over which the phrase is moved, as measured on the foreign side. An exponential penalty of δ^n for movements over n words is added [Koehn et al., 2005]. This distortion model has its limitations, especially in languages such as German and Japanese where reordering over greater distances is more common. Furthermore, some words are more acceptable to be reordered than others; for example an adjective such as "white" may often be reordered in a language in which adjectives appear in a different relative word order to English. A distance distortion model still offers a good starting point for distortion modeling; in fact, capping movement to approximately 4 words leads to BLEU score improvement, even in languages with relatively free word order [Koehn et al., 2005].

C.2.2 Lexical Distortion Models

Many of the limitations of distance based distortion modeling are addressed in lexical distortion models [Tillman, 2004; Koehn et al., 2005], which directly learn the probabilities for a given phrase being reordered relative to adjacent phrases. When collecting phrase pairs we can classify phrases as monotone, swap, or discontinuous based upon the relative placement of the phrases.

Monotone

Forward: word alignment point on bottom right

Backward: word alignment point on top left

Swap

Forward: word alignment point on bottom left

Backward: word alignment point on top right

Discontinuous

Not monotone or swap

Based upon this data, we calculate probability distributions of the form

$$p_r(orientation|\bar{e}, \bar{f}) \tag{C.1}$$

The design space for such a model is inherently larger, and three important design decisions are made in configuring the model, granularity of orientation distinction, side of the translation to condition the probability distribution on, and the directions of orientation to consider. Namely, one can distinguish between all three orientation classes or merely between monotone and non-monotone; one can condition the orientation probability distribution on the foreign phrase or on both the foreign and the source phrase; and one can model with respect to the previous phrase, the following phrase or both. Incorporating a lexical reordering model generally offers significant BLEU score improvements and the optimal configuration depends on language pair [Koehn et al., 2005]. Lexical reordering was analogously implemented in Moses, offering the significant gains in BLEU score detailed below.

Europarl Lang	Pharaoh	Moses
En → De	18.15	18.85
Es → En	31.46	32.37
En → Es	31.06	31.85

C.2.3 Factor Distortion Models

Hard-coding in a few factor based distortion rules to an existing statistical machine translation system, such as forcing the swap of nouns and adjectives when translating from English to Spanish, improves translation quality as measured by the BLEU score [Popović et al., 2006]. This is a motivating result for the development factor distortion models which statistically learn and apply such rules in an analogous manner to the lexical distortion model detailed above.

In factor distortion models we define a reordering model over an arbitrary subset of factors. For example, a part of speech factor distortion model has the ability to learn in a given language that the probability of an adjective being swapped with a noun is high, while the probability of an adjective being swapped with a verb is low. As compared with distance or lexical distortion models, generalizing through a factor distortion model makes better use of the available training data and more effectively models long range dependencies. If we encounter a surface form we have not seen before, we are more likely to handle it effectively through information obtained from its factors. In addition, t is more likely we will have seen a sequence of general factors corresponding to a phrase in our training data than the exact lexical surface form of the phrase itself. As such, by having longer phrases of factors in our training data we have access to reordering probabilities over a greater range, enabling us in turn to model reordering over a greater number of words.

C.3 Error Analysis

We describe some statistics generally used to measure error and present two error analysis tools written over the summer.

C.3.1 Error Measurement

There are three common measures of translation error. BiLingual Evaluation Understudy (BLEU) [Popović et al., 2006], the most common, measures matches of short phrases between the translated and reference text as well as the difference in the lengths of the reference and output. BLEU can be applied to multiple references, but in a way such that BLEU scores using different numbers of references are not comparable.

Word Error Rate (WER) measures the number of matching output and reference words given that if output word i is noted as matching reference word j, output word $i + 1$ cannot match any reference word before j; i.e., word ordering is preserved in both texts. Such a mapping isn't unique, so WER is specified using the maximum attainable number of single-word matches. This number is computable by some simple dynamic programming.

Position-Independent Word Error Rate (PWER) simply counts matching output and reference words regardless of their order in the text. This allows for rearrangement of logical units of text, but allows a system to get away with poor rearrangement of function words.

All these measures are highly dependent on the level of redundancy in the target language: the more reasonable translation options, the less likely the one chosen will match the reference exactly. So the scores we use are really comparable only for a specific source text in a specific language.

Perplexity (defined in Nabhan and Rafea [2005]), measured for a text with respect to a language model, is a function of the likelihood of that text being produced by repeated application of the model. In a shaky sense, he higher the perplexity of a text, the more complex it is, so the harder it is to produce. The perplexity of the output of a modern machine translation system is usually lower (for our test case, by a factor of two to three) than that of a reliable reference translation. This is unsurprising because the people who provide the references have at their command long-range syntactic constructs that haven't been reconstructed via computer.

Along with these statistics, we'd like some assurance that they're stable, preferably in the form of confidence intervals. We use both the paired t test and the more conservative sign test to obtain confidence intervals for the BLEU score of each translation system on a corpus.

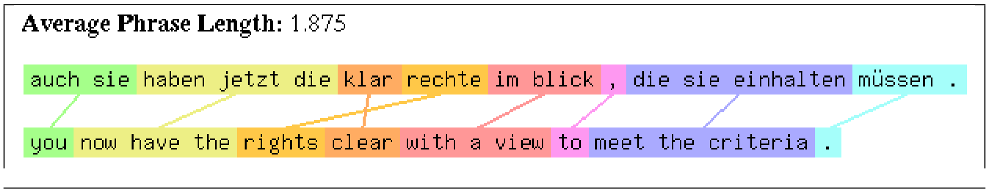
All of these measures can be applied to a text of any size, but the larger the text, the more statistical these scores become. For detail about the kinds of errors a translation system is making, we need sentence-by-sentence error analysis. For this purpose we wrote two graphical tools.

C.3.2 Tools

As part of Koehn's PhD thesis, an online tool was developed that that keeps track of a set of corpuses (a corpus is a source text, at least one system output and at least one reference) and generates various statistics each time a corpus is added or changed. Before the workshop, his system showed BLEU scores and allowed a user to view individual sentences (source, output, reference) and score the output. For large numbers of sentences manual scoring isn't a good use of our time; the system was designed for small corpuses. To replace the manual-scoring feature we created a display of the BLEU scores in detail for each sentence: counts and graphical displays of matching n-grams of all sizes used by BLEU. See Figure C.2 for screenshots.

The overall view for a corpus shows a list of files associated with a given corpus: a source text, one or more reference translations, one or more system translations. For the source it gives a count of unknown words in the source text (a measure of difficulty of translation, since we can't possibly correctly translate a word we don't recognize) and the perplexity. For each reference it shows perplexity. For each system output it shows WER and PWER, the difference between WER and PWER two for nouns and adjectives only (Popovic [2006]), the ratio of PWER of surface forms to PWER of lemmas (Popovic [2006]), and the results of some simple statistical tests, as described above, for the consistency of BLEU scores in different sections of the text. The system handles missing information decently, and shows the user a message to the effect that some measure is not computable. Also displayed are results of a *t* test on BLEU scores between each pair of systems' outputs, which give the significance of the difference in BLEU scores of two systems on the same input.

A second tool developed during the workshop shows the mapping of individual source to output phrases (boxes of the same color on the two lines in Figure C.1) and gives the average source phrase length used. This statistic tells us how much use is being made of the translation model's capabilities. There's no need to take the time to tabulate all phrases of length 10, say, in the training source text if we're pretty sure that at translation time no source phrase longer than 4 words will be chosen.



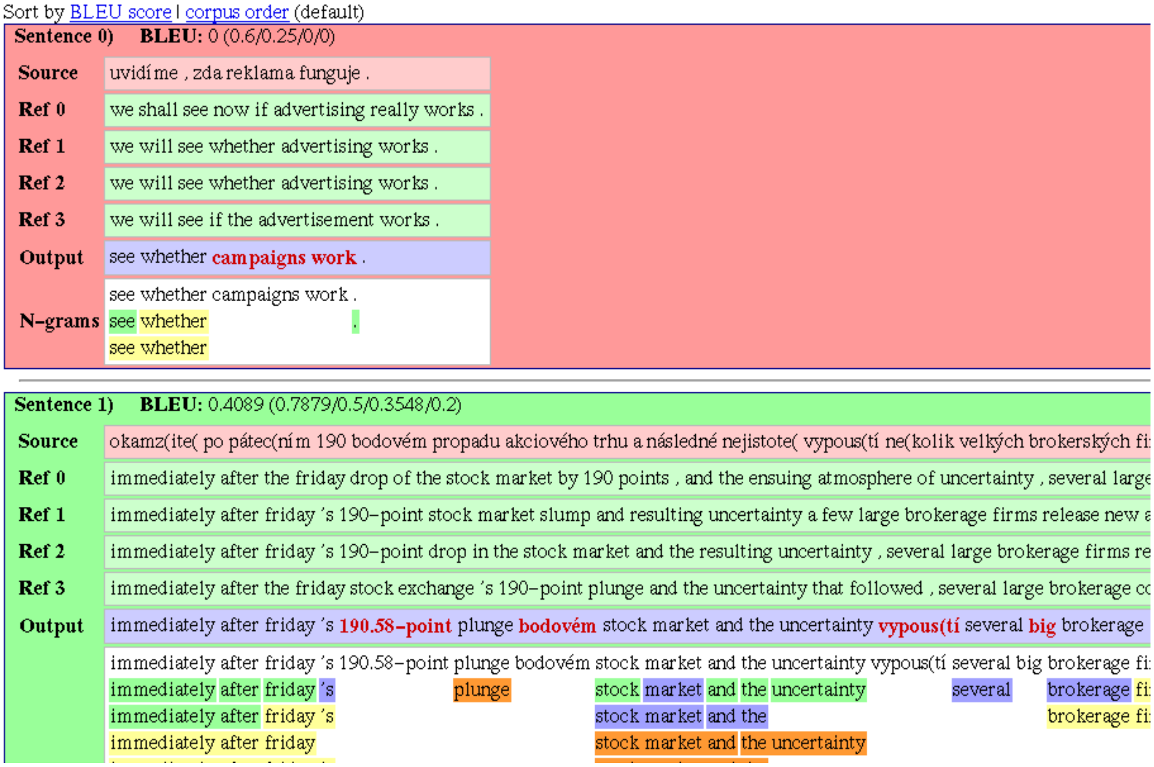
Average Phrase Length: 1.875

```
auch sie haben jetzt die klar rechte im blick , die sie einhalten müssen .

you now have the rights clear with a view to meet the criteria .
```

Figure C.1: Sample output of phrase-detail tool.

Detailed view of sentences



Sort by BLEU score | corpus order (default)

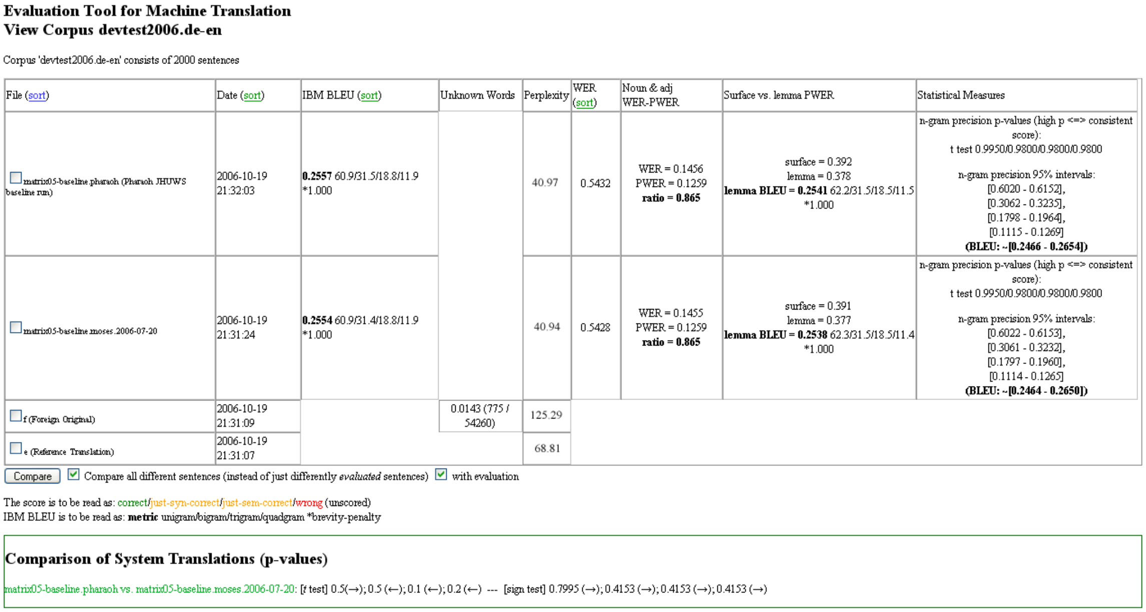
Sentence 0) **BLEU:** 0 (0.6/0.25/0/0)

Source	uvidíme , zda reklama funguje .
Ref 0	we shall see now if advertising really works .
Ref 1	we will see whether advertising works .
Ref 2	we will see whether advertising works .
Ref 3	we will see if the advertisement works .
Output	see whether **campaigns work** .
N-grams	see whether campaigns work . see whether . see whether

Sentence 1) **BLEU:** 0.4089 (0.7879/0.5/0.3548/0.2)

Source	okamz(ite(po pátec(ním 190 bodovém propadu akciového trhu a následné nejistote(vypous(tí ne(kolik velkých brokerských fi
Ref 0	immediately after the friday drop of the stock market by 190 points , and the ensuing atmosphere of uncertainty , several large
Ref 1	immediately after friday 's 190–point stock market slump and resulting uncertainty a few large brokerage firms release new a
Ref 2	immediately after friday 's 190–point drop in the stock market and the resulting uncertainty , several large brokerage firms re
Ref 3	immediately after the friday stock exchange 's 190–point plunge and the uncertainty that followed , several large brokerage co
Output	immediately after friday 's **190.58–point** plunge **bodovém** stock market and the uncertainty **vypous(tí** several **big** brokerage
	immediately after friday 's 190.58–point plunge bodovém stock market and the uncertainty vypous(tí several big brokerage fi immediately after friday 's plunge stock market and the uncertainty several brokerage fi immediately after friday 's stock market and the brokerage fi immediately after friday stock market and the uncertainty

Overall corpus view



Evaluation Tool for Machine Translation
View Corpus devtest2006.de-en

Corpus 'devtest2006.de-en' consists of 2000 sentences

File (sort)	Date (sort)	IBM BLEU (sort)	Unknown Words	Perplexity	WER (sort)	Noun & adj WER-PWER	Surface vs. lemma PWER	Statistical Measures
□ matrix05-baseline.pharaoh (Pharaoh JHUWS baseline run)	2006-10-19 21:32:03	**0.2557** 60.9/31.5/18.8/11.9 *1.000		40.97	0.5432	WER = 0.1456 PWER = 0.1259 **ratio = 0.865**	surface = 0.392 lemma = 0.378 **lemma BLEU = 0.2541** 62.2/31.5/18.5/11.5 *1.000	n-gram precision p-values (high p <=> consistent score): t test 0.9950/0.9800/0.9800/0.9800 n-gram precision 95% intervals: [0.6020 - 0.6152], [0.3062 - 0.3235], [0.1798 - 0.1964], [0.1115 - 0.1269] **(BLEU: ~[0.2466 - 0.2654])**
□ matrix05-baseline.moses.2006-07-20	2006-10-19 21:31:24	**0.2554** 60.9/31.4/18.8/11.9 *1.000		40.94	0.5428	WER = 0.1455 PWER = 0.1259 **ratio = 0.865**	surface = 0.391 lemma = 0.377 **lemma BLEU = 0.2538** 62.3/31.5/18.5/11.4 *1.000	n-gram precision p-values (high p <=> consistent score): t test 0.9950/0.9800/0.9800/0.9800 n-gram precision 95% intervals: [0.6022 - 0.6153], [0.3061 - 0.3232], [0.1797 - 0.1960], [0.1114 - 0.1265] **(BLEU: ~[0.2464 - 0.2650])**
□ f (Foreign Original)	2006-10-19 21:31:09		0.0143 (775 / 54260)	125.29				
□ e (Reference Translation)	2006-10-19 21:31:07			68.81				

Compare ☑ Compare all different sentences (instead of just differently *evaluated* sentences) ☑ with evaluation

The score is to be read as: correct/just-syn-correct/just-sem-correct/wrong (unscored)
IBM BLEU is to be read as: **metric** unigram/bigram/trigram/quadgram *brevity-penalty

Comparison of System Translations (p-values)

matrix05-baseline.pharaoh vs. matrix05-baseline.moses.2006-07-20: [*t* test] 0.5(→); 0.5 (←); 0.1 (←); 0.2 (←) --- [sign test] 0.7995 (→); 0.4153 (→); 0.4153 (→); 0.4153 (→)

Figure C.2: Sample output of corpus-statistics tool.