A framework for phrase based SMT in the technical translation domain

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A Framework For Phrase Based SMT In The Technical Translation Domain

A Thesis Submitted to

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the degree of Master of Science

By

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Professor Ahmed Rafea

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Abstract

Machine translation is not commonly used in the technical translation domain. This is because this domain needs accurate consistent translation based on standard terminologies. Machine translation systems output is not precise and is used only by a user who needs just to understand what the source text is talking about in general.

In the late 90's machine translation research community has reported better results than available commercial MT systems found in the market by using a new approach called statistical machine translation. This approach is language independent and needs no hand crafted linguistic rules. This thesis is interested in researching the statistical machine translation approach and trying to apply it to the problem of the technical translation domain.

We proposed a statistical machine translation system and our experiments using a small corpus of size 20,000 sentences suggested that this system outperforms the well-established word based statistical machine translation system. In a small experiment, we showed that the output of the proposed system is better than the suggestions CAT tools supply to the human translator, and we suggest a new architecture to replace the fuzzy match suggestions found in the available commercial CAT tools.

In future work we need to do more experimentation using the new suggested architecture for the CAT tools. Also we need to enhance the statistical model used in our machine translation system by adding a syntax language model and to experiment the effect of this language model on the performance of the system.

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1. Introduction

Machine translation is the automatic translation of text or speech from one language to another. It is one of the most important applications of NLP. The dream of building machines that let people from different cultures talk to each other easily is one of the most important goals of the NLP community. Unfortunately, MT is a hard problem. It is true that nowadays you can buy inexpensive packages that call themselves translation programs. They produce low-quality translations, which are sufficient for people who know enough about a foreign language to be able to understand the source with the help of a buggy translation.

The goal of many NLP researchers is instead to produce close to error free output that reads fluently in the target language. Existing systems are far from this goal for all but the most restricted domains like weather reports.

1.1 Machine Translation History

The idea of using computers to translate or help translate human languages is almost as old as the computer itself. Indeed, MT is one of the oldest non-numeric applications of computers [Hutchins, J., 1995].

Early proposals for the use of numerical techniques in MT can be traced back at least to 1947, when computers had just been successfully employed in deciphering encryption methods during the Second World War. A memo from Warren Weaver proposed specific strategies for using computers to translate natural languages [Weaver, 1955]. This memo initiated MT research in the USA and the rest of the world, with the first public demonstration of a Russian-English prototype MT system in 1954.

In the 1970's, continued effort in MT yielded operational systems as Systran which was a Russian-English translation system and another system called Meteo began translating weather reports in 1976 [Arturo, T, 1999].

In the late 80's and early 90's a number of companies, especially large Japanese electronics manufacturers, began to market MT software for workstations. A number of products appeared for personal computers, and various Machine-Aided-Translation (MAT) tools such as translation memory began to be commonly used. This period also saw the emergence of work on speech translation and of statistical approaches to machine translation [Arturo, T, 1999].

Late 1990's we are seeing powerful translation engines on personal computers, translation on the Internet, widespread use of translation memory and translator's workbenches, multimedia and software localization, as well as increased interest in Corpus Based MT systems as the statistical machine translation approach [Arturo, T, 1999].

1.2 Machine Translation Strategies

MT systems are normally classified in terms of their basic strategy for carrying out translation [Arturo, T, 1999]. There are three main strategies:

Direct: Direct systems involve extensive string pattern matching, with some re-arrangement of the target string for conformance to the TL word order. Many early systems, as well as some recent MT software for personal computers employ this strategy.

Transfer systems: Transfer systems involve analysis of the source input into a transfer structure which abstracts away from many of the grammatical details of the SL. The idea is to facilitate translation by generalizing over different constructions.

After analysis, the SL structure is transferred into a corresponding TL structure which is then used to generate a TL sentence. Various types of transfer system may be identified, depending on the level at which transfer takes place. In general the more abstract the transfer representation, the easier it is to build the appropriate transfer module

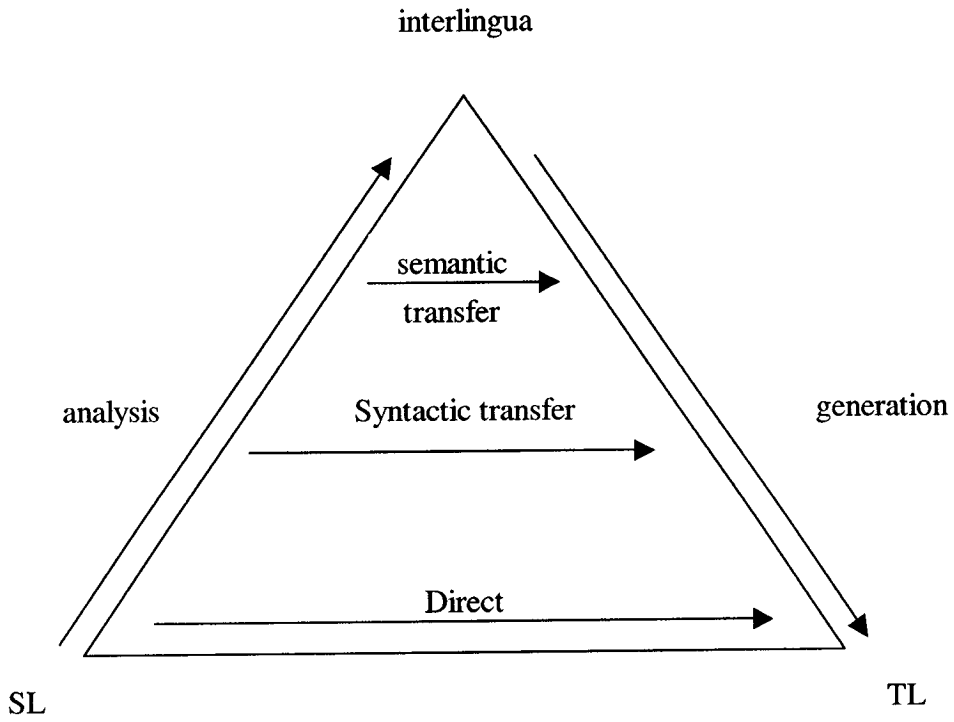


Figure. 1.1: The Vauquois triangle 1

Interlingua: In interlingua systems SL sentences are analysed into a language neutral representation from which generation of TL sentences takes place, possibly after some language-independent manipulation of the interlingua representation. This strategy eliminates the need for a transfer step altogether.

These notions are illustrated using the Vauquois triangle shown in Fig. 1.1. The triangle illustrates in the vertical direction the amount of effort necessary for analysis/generation and in the horizontal dimension the amount of effort needed for

transfer. At the apex, transfer effort is minimum, while analysis and generation are at a maximum.

Obviously, this is a highly idealized view of MT, but it illustrates the point quite neatly. Variations on a basic strategy are possible. For example, a system may use, a hybrid of interlingua and transfer elements. There are also combinations of the basic direct and transfer strategies using statistical and other corpus-based techniques.

1.3 Machine Translation Approaches

We can divide the machine translation implementation approaches into two broad ways

(1) Rule-based MT

(2) Corpus-based MT.

1.3.1 Rule based or Knowledge base MT (RBMT/KBMT)

RBMT is characterized by a heavy emphasis on functionally complete understanding of the meaning of the source text prior to translation to the target text. RBMT/KBMT does not require total understanding, but assumes an interpretation engine can achieve successful translation into several languages. Most RBMT/KBMT is implemented based on the interlingual architecture [Seasly, 2003].

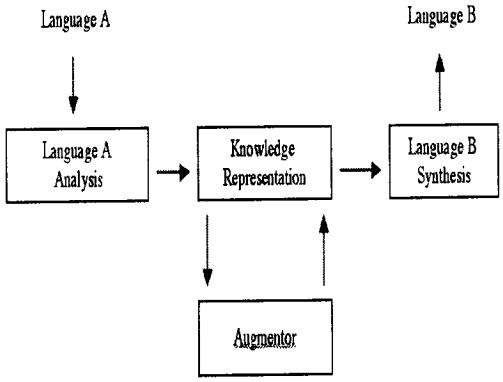


Figure 1.2: RBMT/KBMT symbolic representation

RBMT/KBMT systems must be supported by word knowledge and by linguistic semantic knowledge about meanings of words and their combinations. Thus, a specific language is needed to represent the meanings of sentences. In many RBMT/KBMT systems, knowledge is represented by frames that have named slots or features and values as shown in figure 1.3.

```
[ instance_of: save
  isa:          physical_event
  id:           save_1
  agent:        user
  patient:      [ instance_of: document
                  isa:       separable entity
                  id:        document_1
                  refererence: definite    ]
]
```

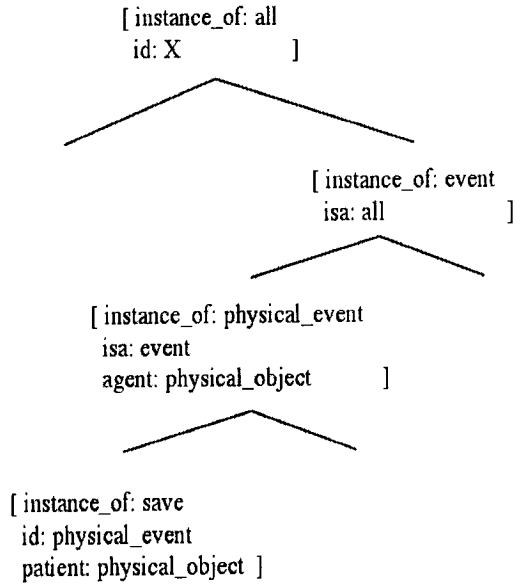


Figure 1.3: Frame hierarchy example [Seasly, 2003]

Once the source language is analyzed, it will be run through the augmenter. The augmenter is the knowledge base that converts the source representation into an appropriate target representation before synthesis into the target sentence. RBMT/KBMT systems provide high-quality translations. However, they are quite

expensive to produce due to the large amount of knowledge needed to accurately represent sentences in different languages.

1.3.2 Corpus Based MT Systems:

The construction of 'traditional' rule based (RBMT) or knowledge-based MT systems (KBMT) is a lengthy, laborious and error-prone process. It is difficult to produce hand-crafted transfer rules to cover a wide variety of input. Frequently, when new rules are added rule conflict can produce unpredictable side effects. In addition, there is no well-known linguistic theory of transfer according to [Melby, 1986]. This led to the idea of translation by analogy principle explained in [Nagao, 1984] and [Sato et al, 1990], which makes use of a set of previously translated sentences (bilingual corpus) as opposed to the construction of hand-crafted monolingual grammars, bilingual lexicons and transfer rules. Since then, there has been an explosion of interest in approaches that use a bilingual corpus as the principal bilingual knowledge source. Such approaches use subtly different techniques and consequently take names to reflect this such as Example based Machine Translation (EBMT), Statistical Machine Translation (SMT) and Translation memory.

1.3.2.1 Translation Memory (TM)

A translation memory is a type of translation support tool and not really a machine translation system. The TM maintains a database of source and target language sentence pairs and whenever it finds a sentence in the text to be translated that exactly matches one of the sentence pairs in the database it automatically retrieves the equivalent target sentence and translates this sentence for the translator.

Translation memory is undeniably useful for the translation of certain types of repetitive documents but this technology as it is right now can only exploit a small portion of the knowledge residing in translators' past production.

A first question that may be raised about this technology is what exactly is meant by an exact match. What qualifies as an exact match between a new source language (SL) segment and the contents of the TM database? In most commercial systems the notion of similarity is based on the number of shared characters or what we can call generally the 'edit distance' between strings. So if we have as in figure 1.4 a sentence (1) to be translated and we got in our TM database sentences (2) and (3) the translation memory will conclude that sentence (1) is matching sentence (2) more than (3) since (2) differs from (1) by only 4 characters although the correct answer should be the reverse.[Macklovitch et. al, 2000].

(1) The wild child is destroying his new toy.

(2) The wild chief is destroying his new tool.

(3) The wild children are destroying their new toy.

Figure 1.4: Translation memory examples

From the previous example, we can conclude that this TM technology could be only useful in translation tasks such as document revisions or updates and perhaps certain types of technical maintenance manuals. Most translators find that this technology is of much help to them but also they are convinced that their archives actually contain much useful information on a sub-sentence level that is not being exploited by these systems.

TM systems are unable to back off and retrieve examples of phrases even though such units may well be present in the database. Suppose that example (4) in figure 1.5 is a new input sentence made up of twenty words. each with the same

length The TM database contains no exact match for (4) but does contain the SL sentence (5). Notice that the two sentences share an identical sub string w1 ... w5 which in both cases is marked off from the rest of the sentence by a comma. However, since this sub string contains only 25% of the sentence's total number of characters, it is doubtful that any current TM system would be able to retrieve it among its fuzzy matches [Macklovitch, 2000].

(4) w1 w2 w3 w4 w5, w6 ... w20

(5) w1 w2 w3 w4 w5,w21 ... w35

Figure 1.5: Fuzzy Matching in TM

1.3.2.2 Structural Example based systems:

EBMT is often linked with the related technique of "Translation Memory" (TM). Some researchers regard EBMT and TM as the same thing, while others believe there is a main difference between the two, rather like the difference between computer-aided translation and MT. Although they have in common the idea of reuse of examples of already existing translations, they differ in that; TM is an interactive tool for the human translator, while EBMT is an essentially automatic translation technique or methodology. They share the common problems of storing and accessing a large corpus of examples, and of matching an input phrase or sentence against this corpus; but having located a (set of) relevant example(s), the TM leaves it to the human to decide what, if anything, to do next, whereas this is only the start of the process for EBMT

The basic idea in structured EBMT is simply to translate a sentence it uses previous translation examples of similar sentences. The assumption being that many translations are simple modifications of previous translations. A fully fledged EBMT

system retrieve more than one example, identify fragments which match parts of the input sentence and combine these fragments into a TL sentence [Somers.,1999].

A typical EBMT system consists of the following main components:

1. An example database of aligned source and target sentences. Translation examples are fully annotated tree structures with alignments at the lexical and structural level. These aligned tree structures serve as the rule base against which parsed SL input sentences are matched. Normally the dependency structure of example sentences may be obtained through manual annotation, or via a parser. Each example includes sub-sentential alignments indicating which fragments between the source and target are in translation correspondence see figure (1.6) below. Again these alignments are made manually or through (semi) automated means using bilingual dictionaries or word and term alignment algorithms.

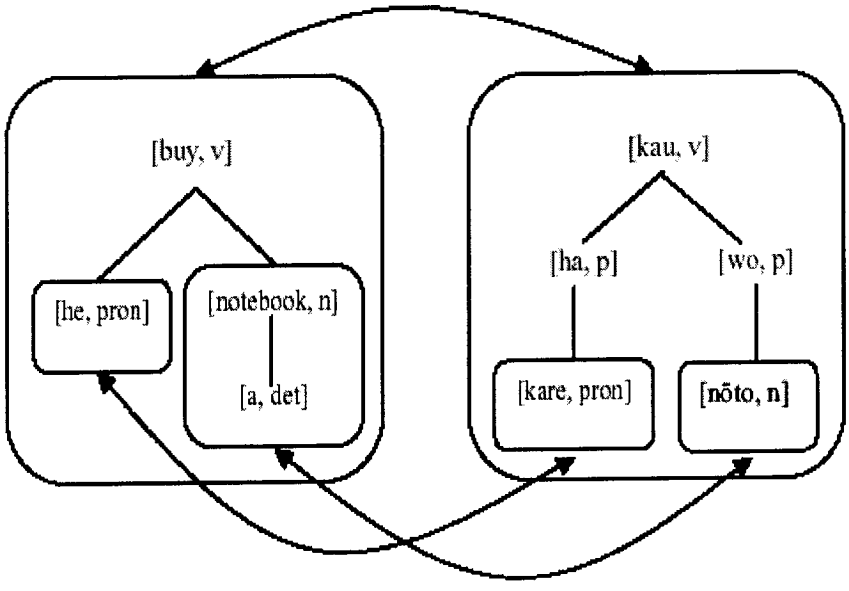


Figure 1.6: Example database in an EBMT [Somers, 1999]

2. A matching algorithm that identifies the examples that most closely resemble all or part of the input sentence. Typically, the closest matching SL structure to the parsed SL input is retrieved. The alignments at the lexical and structural level between translation examples enable the retrieval of translations of segments of the SL input from other translation examples in the corpus. Matching against a set of tree structures is a more complex task than matching against a set of raw translation examples and involves a considerable computational cost. Structural also requires a significant amount of external linguistic knowledge in the form of parsers and perhaps bilingual lexicons. This detracts from portability. However one advantage of including structural information in translation examples is the ability to represent explicitly alignments between languages that indicate a structural divergence
3. A combination algorithm that reconstructs the input sentence through a combination of fragments from the source side of the example sentences.
4. A transfer and composition algorithm that extracts corresponding target fragments and combines them into an appropriate TL sentence.

EBMT is an attractive approach to translation because it avoids the need for manually derived transfer rules. However, it requires analysis and generation modules to produce the dependency trees needed for the examples database and for analyzing the input sentence. Another problem with EBMT is computational efficiency, especially for large example databases, although parallel computation techniques can be applied to solve this problem.

The focus of this research work will be on using corpus-based approaches. These approaches rely on large amounts of bilingual corpora for carrying out translation. The corpus based MT systems tries to extract the linguistic knowledge

needed for translation from the corpus instead of hand crafted rules written by linguists. These approaches have gained a lot of focus during the recent years from the NLP community after reaching a plateau in the research that is dependent on traditional knowledge based systems.

1.4 Motivation

In the area of technical translation and product localization; even the industry leaders are still using only CAT tools in the process of translation of technical documentation, software user interface and online manuals. When we talk about the technical translation into Arabic, which is the focus of this work, MT is for sure not used at all. This is due to the fact that the output of machine translation doesn't help in increasing the productivity of the human translator when compared to the traditional computer aided translation tools which rely only on what is called translation memory technology which is a database of past translations for a specific product.

After the exciting work accomplished over the past decade in the field of Statistical Machine Translation (SMT), Is it still better for translators to use the CAT tools as it is found in the market nowadays or they can benefit more from embedding SMT within the process of localization?

1.5 Thesis objectives

This thesis aim is to answer the following questions:

1) Is it possible to use statistical MT within the framework of the technical translation jobs and give better results than the current CAT tools alone?
2) What is the good architecture of this system? Is it possible to replace the fuzzy logic matching module by the SMT module?
3) The corpus size will not be as large as the general translation domain if we divided the technical domain into more specific areas

such as mobiles, printers, general purpose software, automotive. So a 20,000 sentence corpus will be considered large corpus since it is difficult for a localization company to have access to bigger focused corpus. Will it be possible to get good results using such size of corpus?

4) Can we enhance the quality of the translation by adding simple heuristics in the extraction process of phrases from word alignments similar to Och et. al[1999]. Or this will not be useful in our application.

1.6 Thesis Structure

The thesis will be structured as follows; first chapter 2 will discuss the related work done in the area of interest of this thesis. In this chapter we will review statistical machine translation systems based on the source channel model by explaining different word based translation models , n-gram language models and also different algorithms used to build word based statistical decoders. We will also review phrase based statistical machine translation and give a review about approaches used in building the phrase translation model

Chapter 3 will show the proposed system design and architecture. We will explain the different components that we used in our phrase based translation model and we will show the implementation details of these components together with an explanation of the phrase decoder developed and different decisions taken in the design of the system.

Chapter 4 will present the experimentation results obtained during this work showing how the proposed system outperformed the word based statistical models and

also how we can make use of the proposed system within the framework of technical translation environment that uses CAT tools

Chapter 5 will reach the conclusions of this work together with possible paths that could be taken in future work to enhance the outcome of the proposed system.

Finally, we have included in the appendix samples taken from the output of the developed system together with main source code of the system.

2 Statistical based Translation systems:

The aim of this chapter is to provide an overview and background of the existing approaches to statistical based machine translation systems that are related to this thesis objective.

SMT system constructs a general model of the translation relation that lets the system acquire specific rules automatically from bilingual and monolingual text corpora. These rules are usually coarse and probabilistic. The most established SMT systems are based on word-for-word substitution. An advantage of the SMT approach is that designers can improve translation accuracy by modestly changing the underlying model rather than using large handcrafted resources. [Knight, 1999a]

The switch in the NLP research community from rule based systems to statistical and corpus-based systems started in the end of the 80's and the early 90's with the publication of a very influential paper by a group at IBM [Brown, 1993]. Their statistical model is called a noisy channel model. This model is widely used in signal processing to recover the original signal from a signal with noise

This statistical model (the noisy channel model.) has two central statistical components a source generator and a transfer channel. A source signal generator generates a signal according to a statistical model and a transfer channel corrupts the signal according to a statistical channel model. The parameters of the models can be obtained from samples of the generated signal and the input output pairs of the transfer channel. Given the parameters of the statistical models, one can recover the original signal from an observed noisy signal, the output of the transfer channel.

This idea can be applied to statistical machine translation, such as a French to English translation system. In the noisy channel model, we use a well formed English

sentence generator and an English to French transfer channel. Hence, we consider that the channel corrupts an English sentence and modifies it to appear as French. The task of machine translation system is to recover the original English sentence from an observed French sentence

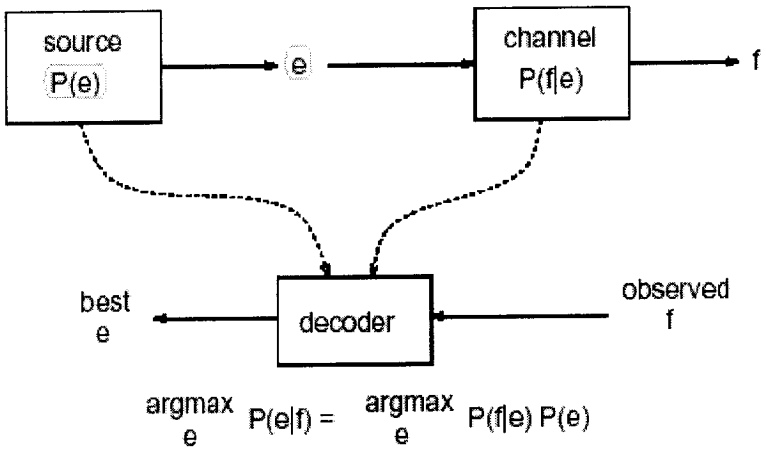


Figure 2.1 : Noisy channel model []

Figure 2.1 illustrates this process. The upper left box generates a well formed English sentence e, with probability P(e). This sentence is subsequently translated into a French sentence f in the channel (the upper right box) with probability P(f|e). The goal of translation (or decoding) is to recover the original e given an observed sentence f. Any sentence e can be a potential translation of f, but some are more probable than others. We aim to select the most probable e which gives the highest P(e|f), or using bayes rule equivalently the highest **P(f|e) . P(e).**

A typical Statistical Based Machine Translation system consists of the following main components:

1) A **Language model** that is responsible for calculating the P(e) so as to ensure that the outcome of the translation is syntactically correct
2) A **Translation model** that is responsible for calculating the P(f|e) we have to know that the translation model doesn't necessarily turn e into good f since

part of this problem is the responsibility of the independently trained language model

3) **A decoder** which is responsible to translate an observed foreign sentence into the source sentence this is done by calculating argmax P(e) . P(f|e) for all possible e. This process is called decoding. It is impossible to search through all possible sentences, but it is possible to inspect a highly relevant subset of such sentences using heuristic search techniques. So what we get at the end is the most likely translation.

2.1 Language Model

Concerning the Language modeling we need to build a machine that assigns a probability P(e) to each e sentence. The statistical language model is based on this simple idea. Just record every sentence that anyone ever says in the language. Suppose you record a database of one billion sentences. If the sentence "how's it going?" appears 76,413 time in that database then we say P(how's it going?) = 76,413/1,000,000,000 = 0.000076413. We can use the web to build the needed monolingual corpus. So by this a sentence as "I like snakes" is less probable than "I hate snakes". The most widely used statistical language modeling is N-grams. In this model a string is broken down into components (substrings) and n word substring is called n-gram. If n=2 we say bigram, if n=3 we say trigram. If a string contains a lot of reasonable n-grams then maybe it is a reasonable string. I will explain the bigram language model by an example [Knight, 1999a] and this can be generalized to n-gram language models.

Let b(y | x) be the probability that word y follows word x. We can estimate this probability from online text. We simply divide the number of times we see the phrase "xy" by the number of times we see the word "x". That's called a conditional bigram

probability. Each distinct b(y | x) is called a parameter.

A commonly used n-gram estimator looks like this:

b(y | x) = number-of-occurrences("xy") / number-of-occurrences("x")

P(I like snakes that are not poisonous) ~

. b(I | start-of-sentence) *

b(like | I) *

b(snakes | like) *

...

b(poisonous | not) *

b(end-of-sentence | poisonous)

In other words, what's the chance that you'll start a sentence with the word "I"? If you did say "I", what's the chance that you would say the word "like" immediately after? And if you did say "like", is "snakes" a reasonable next word? And so on. [Knight, 1999a]

2.2 Translation model

We can divide the statistical machine translation approach broadly into two main models depending on the algorithm used in the translation model and decoding components. The first one can be named as single-word based models (SWB). Models of this kind assume that an input word is generated by only one output word as [Brown, 1993]. This assumption does not correspond to the nature of natural language where in some cases we need to know a word group in order to obtain a correct translation. One initiative for overcoming the above restriction of single word models is known as the template based approach where still the underlying model is based on single word translation table. [Och, 1999] In this approach an entire group of adjacent

words in the source sentence may be aligned with an entire group of adjacent target words in the target sentence. A template establishes the reordering between two sequences of word classes.

Recent works in the area of statistical based translation presented what is called the phrase-based statistical approaches [Koehn, 2003]. These methods explicitly learn the probability of a sequence of words in a source sentence being translated to another sequence of words in the target sentence.

2.2.1 Word based statistical translation models

Now I will give a brief description about the IBM translation models 1,2,3,4,5, which are the well known word based models in the statistical machine translation area. A full description could be found in [Brown, 1993] and their decoding algorithm in [Berger, 1996].

Model 1 is the simplest model, and later models are extensions to previous models. All models are word-based models. The input and output of the channel is just sequences of words, and the channel operations are word duplication (including insertion and deletion, word movements and word translations. To follow is a brief description for each model [Knight, 1999a].

Fig 2.2 illustrates how Model 1 works. First the length of the target word sequence is determined (the target in the noisy channel refers to the source in normal translations) based on the source length. Next each output position is filled by copying one of the source words. This copy operation works as word-duplication and word movement.

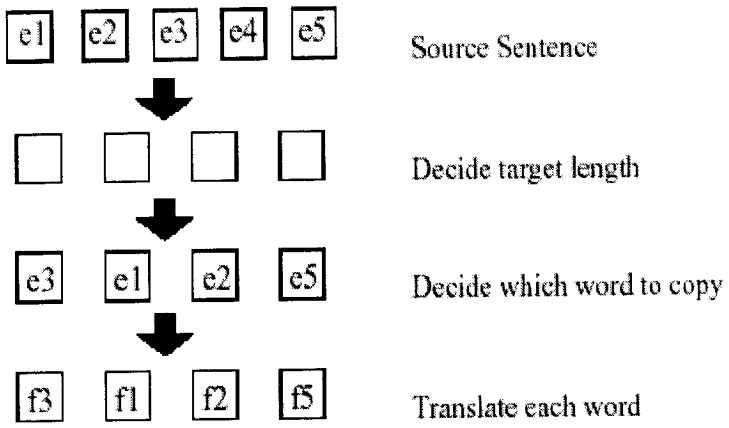


Figure. 2.2: IBM Model 1

Source word maybe copied more than once. Some of the source words may not be copied to the target. This model and all subsequent models assume that a special word NULL exists in the source sentence, copying the NULL word acts as word insertion. The probability of copying a source word is assumed uniform. After the target positions are filled the words are translated independently according to a word translation table t(f|e).

Model 2 extends Model 1 by employing a more general probability table for the copy operation rather than the uniform probability as in Model 1.This probability is conditioned on the source and target length a(sourcePosition| targetposition, sourceLength, targetLength)

Model 3 introduces a new parameter called word fertilities, which controls the number of word duplication operation based on the source word see figure 2.3.

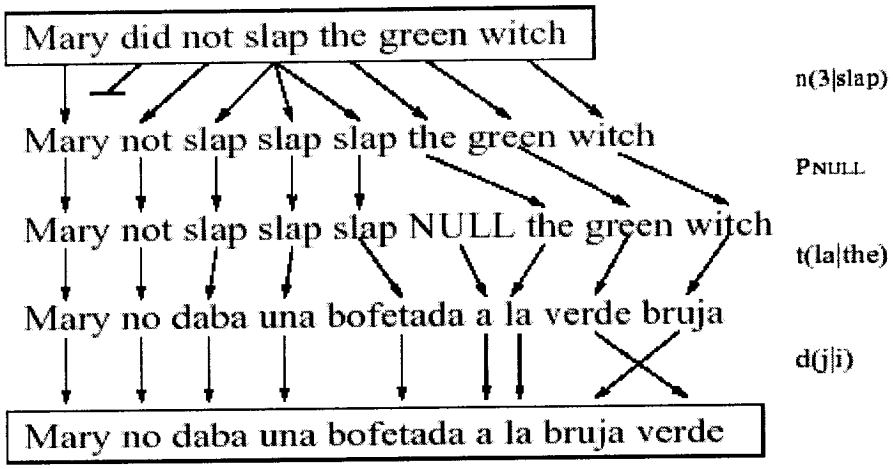


Figure 2.3: IBM Model 3 from [Yamada,2001]

In model 3 the word move operations probabilities are given by the table d(targetPosition| SourcePosition, targetLength, sourceLength) which is called the distortion table

In model 4, the distortion table is divided into two tables; d1 and d>1. Figure 2.4 shows how these tables are used. A source word is called fertile if its fertility is greater than zero.

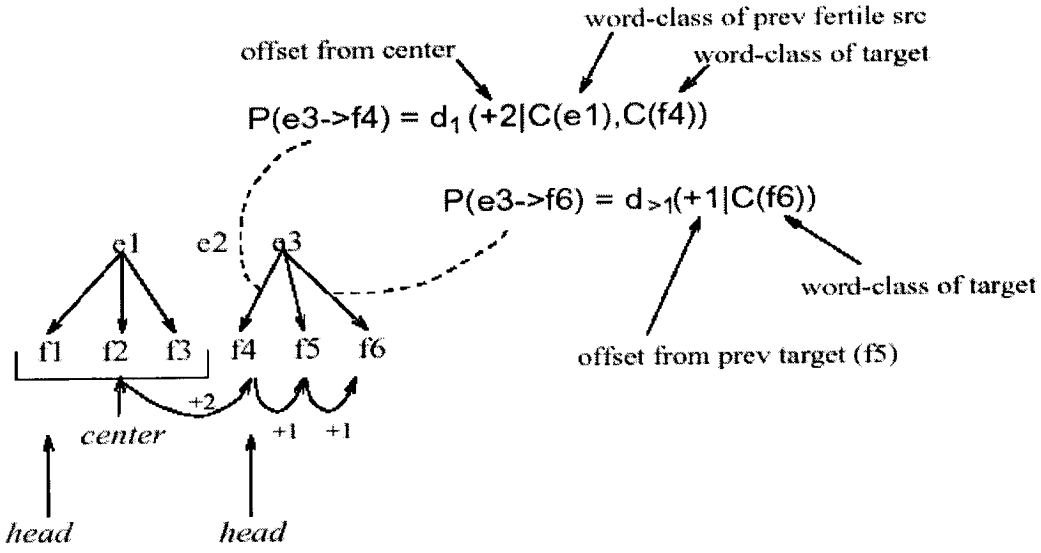


Figure.2.4: Model 4 distortions

In figure 2.4 the words e1 and e3 are fertile. The leftmost target position for a fertile word is called the head, and the average of the target positions for a fertile word is called the center. The target words f1 and f4 are the heads, and the center for e1 is the position where f2 is placed. The distortion table d1 is used to decide the position of heads, and the d>1 is used for non-heads. The d1 table specifies the offset from the center for the previous fertile word and is conditioned on the word classes of the previous fertile word and the target word. The word classes C() are automatically derived using a clustering algorithm [Brown, 1993]. The d>1 is similar but the offset is measured from the previous target position and is conditioned on the word class of the target word. Using offsets rather than absolute positions rewards whole phrasal movements.

Model 5 is basically the same as Model 4, except it adjusts the probabilities to avoid deficiency. The distortion probability table allows moving more than one source words into the same target position since each word move is independent form others so in Model 5 additional variables are introduced to represent vacant and valid target positions and to enforce a source word is copied only to a vacant and valid position.

2.2.2 Phrase based Statistical Machine Translation models

The principal innovation of the phrase based translation model is that it attempts to calculate the translation probabilities of word sequences rather than of only single words as IBM models [Koehn, 2003]. The other property of this translation model is that the alignment between phrases is one to one and continuous.

The generative process, which allows for the translation of a sentence, can be broken down into the following steps: First, the input sentence is segmented into phrases. Then each phrase is translated to the corresponding output phrase. The output

sentence is made by concatenating and reordering the output phrases to generate the target sentence.

During the last couple of years the statistical machine translation community has tried to enhance the translation output of IBM models by adding the concept of phrase to the translation model and also by adding lexical, syntax and semantic knowledge to the system. Some of the approaches could be found in [Marcu, 2002] and [Koehn, 2003]

The idea of phrase based SMT and adding external linguistic knowledge to the system was thought about to try to solve a number of challenges faced by the pure word-based statistical translation models as follows:

- The first problem is with multiple English words being translated from a single foreign word, which is not allowed by the IBM alignment scheme.
- The second is the translation of multiple word phrases which do not decompose easily into word for word translations because of non-compositional semantics.
- Finally, a practical problem in the estimation of the parameters of the IBM model is that only reordering local to an area of a few words can be estimated with any accuracy, making larger syntactic transformations difficult to capture.

It is very hard to address these challenges within the word based statistical machine translation framework. All of the parameters are tied to words, and these problems are tied to the behavior of groups of words which are called "chunks" and which might be described using linguistic vocabulary such as verb group or noun

phrases. The behavior of chunks is above the word level, and IBM model fails to capture this behavior.

Various researchers have improved the quality of statistical machine translation systems with the use of phrase or chunk machine translation. Most recently published methods [Zens, 2002] , [Venugopal, 2003] and [Koehn, 2003] on extracting phrase translation tables from a parallel corpus start with a word alignment.

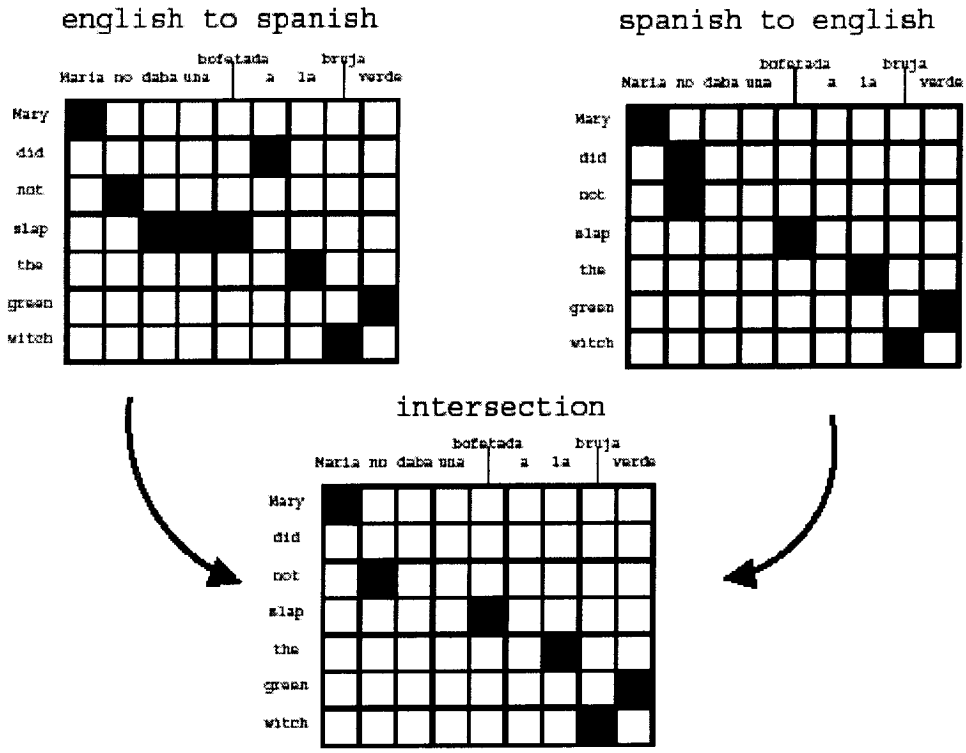


Figure 2.5: Phrase extraction heuristics

The main idea is to align the parallel corpus bi-directional e.g. Spanish to English and English to Spanish as show in the above figure [2.5]. This generates two alignments that have to be reconciled. If we intersect the two alignments, we get high precision alignments with low recall and if we do the union, we get a high recall with low precision alignments. To extract phrases from these word alignments researchers consider any continuous block of words aligned to another continuous block in the

target words is considered a phrase. By this, they generate Phrase translation table to be used together with the word translation table.

2.3 Decoder for statistical machine translation

A good decoding algorithm is critical to the success of any statistical machine translation system. The decoder's job is to find the translation that is most likely according to a set of previously learned parameters. If we observe a new sentence f, then an optimal decoder will search for an e that maximizes P(e|f) ~ P(e) . P(f|e)

The decoding problem in statistical machine translation can be divided into two sub problems. The first is selecting a concise set of source words according to the P(f|e) and the other is selecting a good source word order based on the P(e) According to Knight [1999b] The first sub problem is like solving the minimum set coverage problem. See figure [2.6] And the other problem is like solving the traveling salesman problem. see figure [2.7]

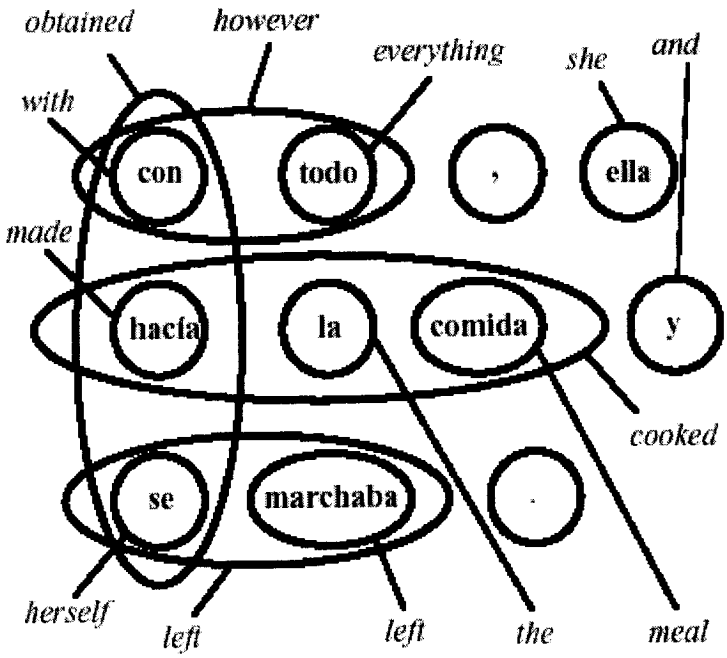


Figure 2.6: The minimum set problem [Kinght, 1999b]

Selecting a Concise Set of Source Words is Like Solving the Minimum Set Cover Problem. A channel model "Translation model" with overlapping one to many dictionary entries will typically license many decodings. The source model may prefer short decodings over long ones. Searching for a decoding of length =< n is difficult resembling the problem of covering a finite set with a small collection of subsets. In the example shown above the smallest acceptable set of source words is { she and cooked however left comma period}

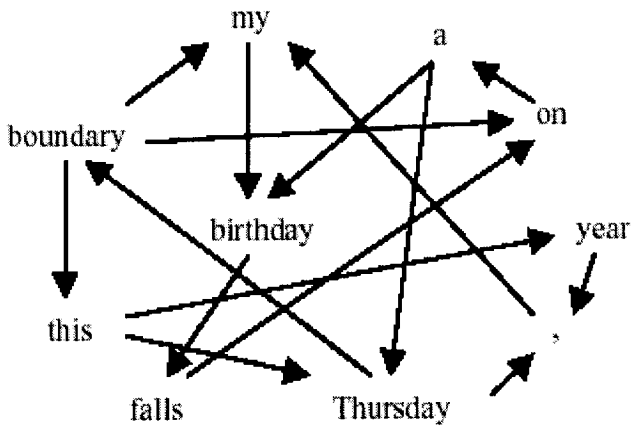


Figure 2.7: Word reordering seen as TSP [Kinght, 1999b]

If we assume that the channel model offers deterministic word for word translations then the bigram source model takes responsibility for ordering them. Some word pairs in the source language may be illegal. In that case finding a legal word ordering is like finding a complete circuit in a graph. In the graph shown above a sample circuit is boundary -> this -> year ->comma -> my -> birthday -> falls -> on -> a -> Thursday -> boundary. If word pairs have probabilities attached to them then word ordering resembles finding the least cost circuit also known as the Traveling Salesman Problem

Since these two problems are proved to be NP-complete then to build a statistical machine translation it is possible to devise approximation algorithms like those devised for other NP Complete problems. So far statistical translation research has used heuristic beam search algorithms to solve these problems. To follow is a brief explanation for these algorithms

2.3.1 Stack Decoding

The stack decoding (also called A*) decoding algorithm is a kind of best-first search which was first introduced in the domain of speech recognition [JeLinek, 2001] The generic stack decoding algorithm is as follows:

1. Insert into the stack all the single-branch paths corresponding to the input string according to the translation lexicon. Arrange the entries in a descending order
2. Take the top entry off the stack. If this entry is a complete translation then stop –this is the best path- else evaluate all possible next word extensions and insert them into the stack in a descending order
3. Repeat the above step until the stopping criterion in step 2 is satisfied.

One crucial difference between the decoding process in speech recognition and machine translation is that speech is always produced in the same order as its transcription. Consequently, in speech recognition decoding there is always a simple left-to-right correspondence between input and output sequences. This change makes decoding significantly more complex in machine translation. Instead of knowing the order of the input in advance we must consider all n! permutations of n-word input sentence.

Another important difference between speech recognition and MT decoding is the lack of reliable heuristics in MT. A heuristic is used to estimate the cost of

completing a partial hypothesis. A good heuristic makes it possible to accurately compare the value of different partial hypothesis and to focus the search in the most promising direction. The left to right restriction in speech recognition makes it possible to use a simple yet reliable heuristics which estimate cost based on the amount of input left to decode. Without a heuristic a classic stack decoder will almost always find that shorter hypothesis looks more attractive than longer ones since as we add more words we end up multiplying more and more terms to find the probability so longer hypothesis will be at the end of the stack. So to solve this issue Germann et. al [2001] used more than one stack to force hypothesis to complete fairly. They had one stack for each subset of input words. This way a hypothesis can only be pruned if there are other better hypothesis that represent the same portion of the input. At each iteration they choose one hypothesis from each stack to be extended.

The stack decoder for Model 3 builds the translation incrementally by applying operations to hypothesis. The decoder used four operations:

- **Add** adds a new English word and aligns a single French word to it.
- **AddZfert** adds two new English words.The first has fertility zero, while the second is aligned to a single French word.
- **Extend** aligns an additional French word to the most recent English word, increasing its fertility.
- **AddNull** aligns a French word to the English NULL element.

To reduce the cost of AddZfert they considered only certain English words as a candidates for zero-fertility basically words which both occur frequently and have a high probability of being assigned null alignment. This was extracted from the training data. Second they only used zero fertility words if it increases the language model probability more than decreasing the alignment probability.

2.3.2 Fast Greedy decoding

Another alternative for solving many instances of NP-complete problems is the greedy method. Instead of deeply probing the search space, such greedy methods

typically start out with a random approximate solution and then try to improve it incrementally until a satisfactory solution is reached.

The greedy decoder developed by Germann et. Al [2001] starts the translation process from an English gloss of the French sentence given as input. The gloss is constructed by aligning each French word fj with its most likely English translation efj (efj = argmaxet(e|fj)). For example, in translating the French sentence "Bien entendu , il parle de une belle victoire .", the greedy decoder initially assumes that a good translation of it is "Well heard , it talking a beautiful victory" because the best translation of "bien" is "well", the best translation of "entendu" is "heard", and so on. Once the initial alignment is created, the greedy decoder tries to improve it by applying one of the following operations:

- **translateOneOrTwoWords(j1,e1,j2,e2)** changes the translation of one or two French words, those located at positions j1K and j2 from efj1 and efj2 into e1and e2 . If efj 1 is a word of fertility 1 and ek is NULL, then efj 1 is deleted from the translation. If efj 1 is the NULL word, the word ek is inserted into the translation at the position that yields the alignment of highest probability. If efj1 = e1 or efj2 = e2, this operation amounts to changing the translation of a single word.

- **translateAndInsert(j,e1,e2)** changes the translation of the French word located at position j from efj into e1 and simultaneously inserts word e2 at the position that yields the alignment of highest probability. Word e2 is selected from an automatically derived list of 1024 words with high probability of having fertility 0. When efj = e1 this operation amounts to inserting a word of fertility 0 into the alignment.

- **removeWordOfFertility0(i)** deletes the word of fertility 0 at position i in the current alignment.

- **swapSegments(i1,i2,j1,j2)** creates a new alignment from the old one by swapping non-overlapping English word segments[i1,i2] and [j1,j2]. During the swap operation, all existing links between English and French words are preserved. The segments can be as small as a word or as long as |e| -1 words, where |e| is the length of the English sentence.

- **joinWords(i1,i2)** eliminates from the alignment the English word at position i1 (or i2) and links the French words generated by ei1(or ei2) to ei2(or ei1).

In a stepwise fashion, starting from the initial gloss, the greedy decoder iterates exhaustively over all alignments that are one operation away from the alignment under consideration. At every step, the decoder chooses the alignment of highest probability, until the probability of the current alignment can no longer be improved. When it starts from the gloss of the French sentence "Bien entendu, il parle de une belle victoire.", for example, the greedy decoder alters the initial alignment incrementally as shown in Figure [2.8], eventually producing the translation "Quite naturally, he talks about a great victory.". In the process, the decoder explores a total of 77421 distinct alignments/ translations, of which "Quite naturally, he talks about a great victory." has the highest probability.

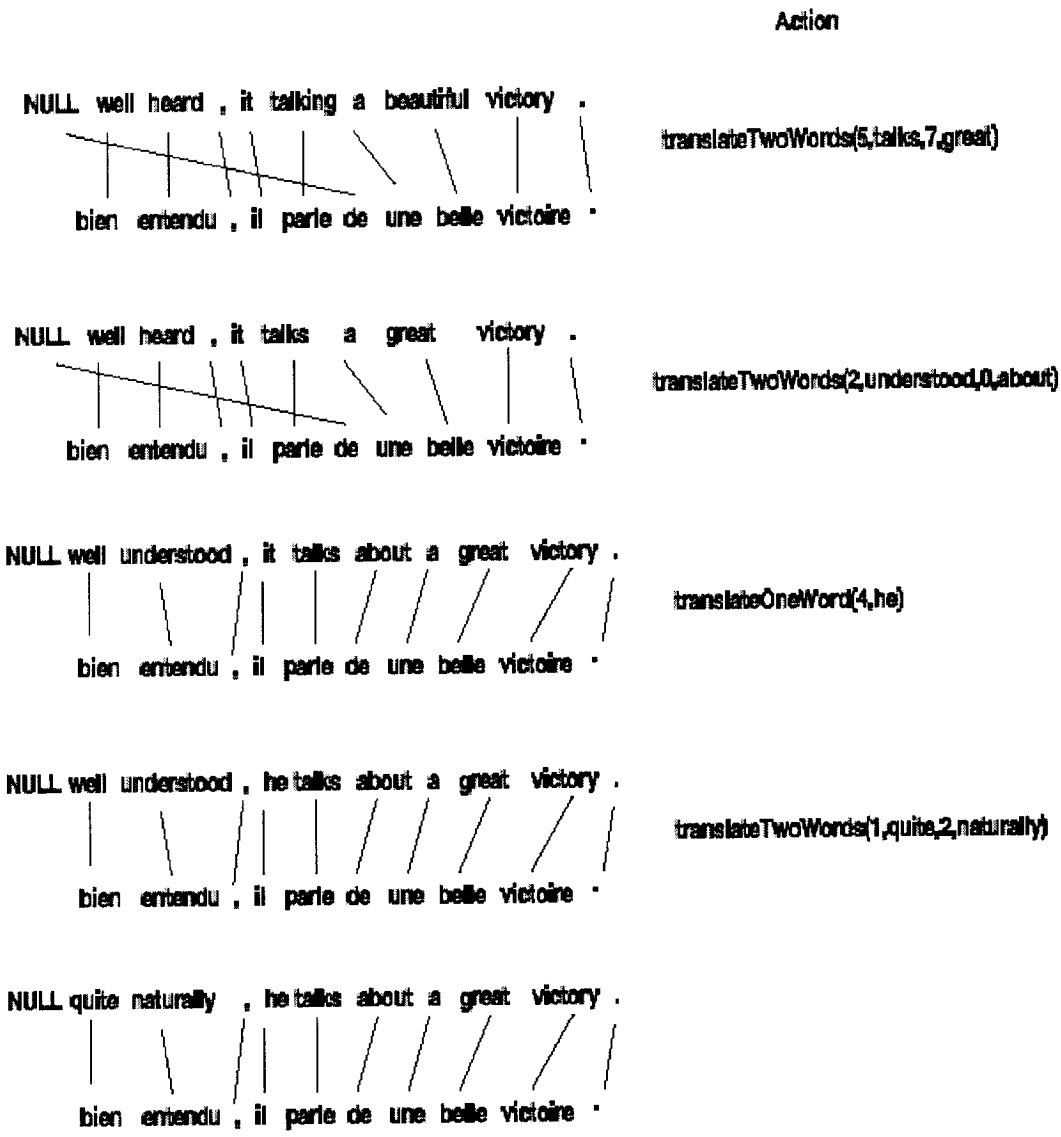


Figure 2.8: Fast Greedy decoder illustration [Germann, 2001]

The greedy decoder [Germann, 2001] is a viable alternative to the traditional stack decoding algorithm. Even when the greedy decoder used a set of operations that is optimized for speed in which at most one word is translated, moved or inserted at a time and at most 3 word long segments are swapped the translation accuracy is affected only slightly. In contrast, the translation speed increases at least one order in magnitude. We can consider the greedy decoder as a hill climbing algorithm for decoding.

2.3.3 Phrase based decoder

The phrase decoder that was developed and discussed in [Koehn, 2003] used the stack decoding discussed previously as its base algorithm. During decoding, the foreign sentence is segmented into a sequence of I phrases and each foreign phrase is translated into an English phrase. The English phrases may be reordered according to the relative distortion probability distribution $d(a_i - b_{i-1})$ where a_i denotes the start position of the foreign phrase that was translated into the ith English phrase and b_{i-1} denotes the end position of the foreign phrase translated into the (i-1)th English phrase.

The phrase decoder is using Bayes rule $P(e|f) = \text{argmax}_e\ p(f|e)\ p(e)$

Where p(f|e) is decomposed into

$$\mathbf{Pr}((f'^{I}_{1}|e'^{I}_{1}) = \prod_{i=1 \text{ to } I} \mathbf{p}(f'_i|\, e'_i)\ \mathbf{d}(a_i - b_{i-1})$$

In order to make the computation tractable they prune weak hypothesis from the stack based on the cost they incurred so far and a future cost estimate. Also they use a beam size of n best hypothesis uptill now any hyposthesis lower than this n beam size is removed from the stack.

The cost of a hyposthesis is calculated based on the P(e|f) of this hyposthesis up to this point and the future cost estimate which is calculated by first extracting all translation options (phrase translation) that is valid for the current input sentence then store these translation options together with their cost which is the phrase translation probability multiplied by the language model for this phrase only and ignoring the distortion probability $\mathbf{d}(a_i - b_{i-1})$.

3. A Proposed SMT

We chose to use the SMT approach since it can learn language rules automatically and without the need of language experts. Moreover according to recently published results IBM SMT system outperformed classical rule based machine translation systems during a recently held MT competition

In order to be able to have a functioning SMT system we need to have a training bilingual corpus and to have a translation model and accordingly develop an SMT system. Finally we should have a methodology for evaluating system output and report the results. In this chapter we will explain our different system components and the concept behind this design.

3.1 Training Corpus collection

Since this work is interested in the performance of statistical MT in the technical translation domain and in order to develop a statistical MT system we need to have a training corpus that should be from the same domain for which the MT system is used I was able to collect translation memories of previously translated technical documentation in the areas of mobile phone documentation and software, computer printers documentation and software, and automotive documentation. These TMs were translated from English to Arabic. The statistics of this corpus could be found in table 3.1 below.

In order to be able to use the translation memories we had to develop some macros to extract a sentence aligned corpus after removing as much as possible all the noise found in these TMs. This noise was due to the TM file formats, which include many tags that is related to the formatting of the text and has no relation with the translation itself.

Domain	Sentences	Words	Vocabulary
Mobile Phones	19148	149127	9558
Printers	19840	228555	13720
Automotive	18634	220205	13276
All (Joined corpus)	57622	780770	29709

Table 3.1: Corpus statistics

3.2 Generic SMT system components

One of this work objectives is to evaluate the performance of the word based SMT systems and take it as a baseline to compare it with the phrase based systems. We had to build the standard word based SMT systems. You can see the basic architecture for this type of systems in figure 3.1 below.

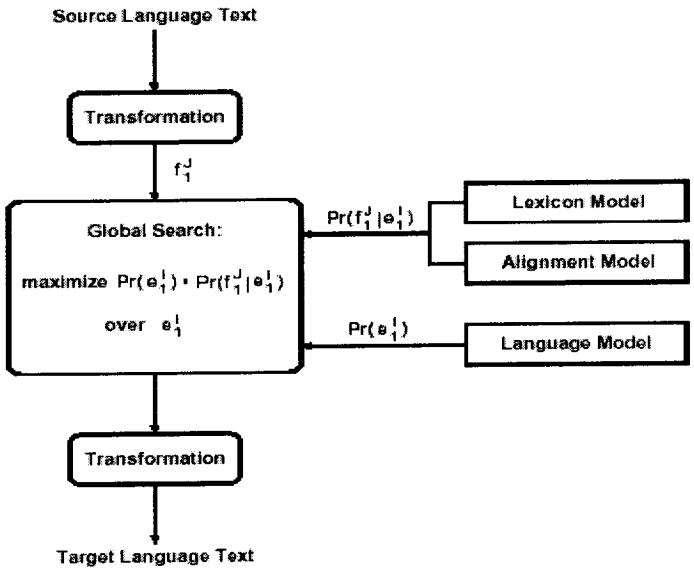


Figure 3.1: SMT architecture based on Bayes' descision rule

We can see from the generic architecture that we need to have several components to be able to have a running SMT systems based on the source channel approach. During the experimentation of this work, we used the GIZA++ freely

available toolkit which implements the lexicon and alignment model based on IBM models 1 through 4 discussed in chapter 2 of this thesis. GIZA++ is an extension to the program GIZA part of the SMT toolkit "EGYPT" developed by the statistical machine translation team of ISI/USC university during a summer workshop in 1999 at the center for language and speech processing at John Hopkins university [Al-Onaizan et al, 1999]

. The GIZA++ was written and designed by Franz Och and can be downloaded from:

http://www-i6.informatik.rwth-aachen.de/Colleagues/och/software/GIZA++.html

For the decoding component, which is shown in figure 3.1 as the global search problem, we used the ISI Rewrite greedy decoder developed in ISI/USC [Germann, 2001] and discussed in chapter 2 of this thesis. This decoder works with the output files of the GIZA++ toolkit.

3.3 The proposed system components

In this work, we want to see how much can we enhance the SMT performance by adding phrase translation knowledge to the system.

Koehn et. al in [Koehn, 2003] suggest that the highest levels of performance can be obtained through relatively simple means: heuristic learning of phrase translations from word-based alignments and lexical weighting of phrase translations. Surprisingly, learning phrases longer than three words and learning phrases from high-accuracy word level alignment models does not have a strong impact on performance. Learning only syntactically motivated phrases degrades the performance of the proposed systems." So we decided to use the simple phrase based method described by Franz Och et al.in [Och, 1999] and [Kohen, 2003] in order to evaluate how much the state of the art phrase based statistical machine translation can enhance

the productivity and help the human translators in the domain of technical translations. The proposed system architecture can be shown in figure 3.2

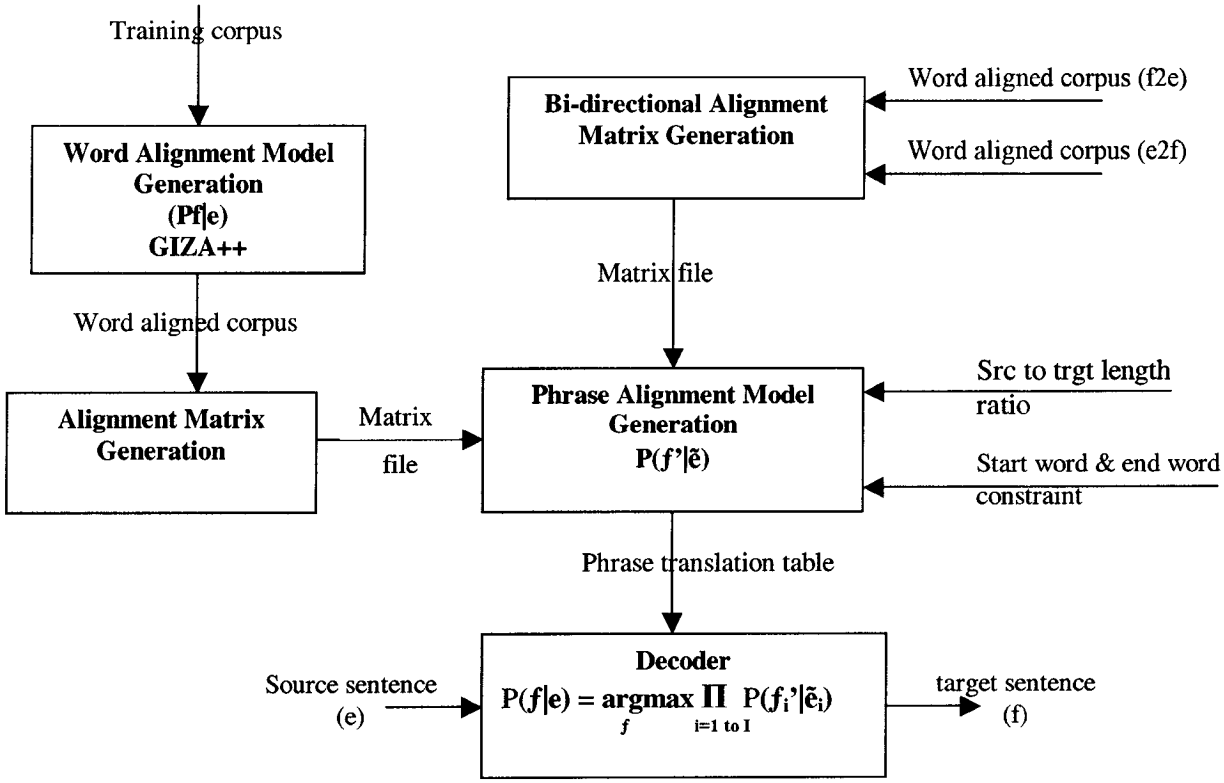


Figure 3.2: The proposed system architecture

3.3.1 Alignment Matrix generation

In order to train the phrase alignment model that will be used by the decoder later we had to develop the first component of our phrase based machine translation system, which was the alignment matrix generation shown in figure 3.2.

The alignment matrix generation tool uses the word alignment file generated by the GIZA++ toolkit as an input to generate what we call the matrix file that contains for every sentence aligned in the corpus a matrix showing the alignment. If a source word ei is aligned with a target word fj we place 1 in matrix position [i,j] see figure 3.3

$	1	0	0	0	0	0
spark	0	0	0	1	1	0
plug	0	0	0	0	0	0
tightening	0	0	1	0	0	0
torque	0	1	0	0	0	0
:	0	0	0	0	0	1
	$	عزم	ربط	شمعة	الإشعال	:

Figure 3.3: Alignment Matrix

3.3.2 Bi-directional Alignment Matrix generation

We implemented another module that could be used in building the word alignment matrix. This module is the implementation of the algorithm explained by Franz Och et al in [Och, 1999] as follows; after aligning a parallel corpus bi-directionally using GIZA++; construct the intersection matrix of the two word alignments generated and then add new alignment points that exist in the union of two word alignments if these points satisfies the following two constraints:

1.A new alignment point is added if it connects at least one previously unaligned word in the intersection.

2. And this new alignment point is directly adjacent to an already existing alignment point in the intersection.

3.3.3 Phrase alignment generation model

Before describing the algorithm used in the training of the phrase alignment model, we have first to define what a bilingually aligned phrase means. A bilingual phrase is defined as a pair of m consecutive source words that has been aligned with n

consecutive target words with the exception that any null aligned word will be included in the phrase.

In table 3.2 we can see the phrases extracted from the aligned sentence shown in figure 3.3. We have included in Appendix A of this thesis also part of the phrase table generated from the proposed system.

- For I = MaxsPhraseLen downto 1 Do
  - Init TotalNumPhrases //Total number of extracted phrases
  - For all aligned sentences in the Matrix file Do
    - For J=0 to (SrcLen – I) Do //extract all possible phrases of len I
      - Init MinTrgtIdx & MaxTrgtIdx
      - For K=1 to I Do //Loop over SrcPhrase
        - AddSrcIdx
        - GetAlignTrgt(K+J, MintrgtIdx,MaxTrgtIdx)
      - GetNullAlignedTrgt(MintrgtIdx,MaxtrgtIdx)
      - If ContineousPhrase = True then
        - If SrcPhrase = found then
          - Increment N_e(SrcPhrase)
        - Else Increment TotalNumPhrases
        - If BilingualPhrase = found then
          - Increment N_f_e(BilingualPhrase)
        - Else
          - AddtoPhraseTable
          - Set N_f_e(SrcPhrase) =1
- For I = 1 to TotalNumPhrases
  - For every BilingualPhrase of current SrcPhrase
    - Set $\mathbf{P(f' | \tilde{e}) = N(f', \tilde{e}) / N(\tilde{e})}$

where $N(\tilde{e})$ denotes the number of times phrase $\tilde{e}$ has appeared and $N(f', \tilde{e})$ is the number of time the bilingual phrase $f' \& \tilde{e}$ has appeared

Figure 3.4 : Phrase table generation algorithm

The basic algorithm used in the generation of the phrase translation table is shown in figure 3.4 above and we have included in Appendix B the main classes and functions used in the development of the proposed system.

Spark plug tightening torque	عزم ربط شمعة الإشعال
Plug tightening torque	عزم ربط
Spark plug tightening	ربط شمعة الإشعال
tightening torque	عزم ربط
Spark plug	شمعة الإشعال
Plug tightening	ربط

Table 3.2: Example of extracted aligned phrases

In the figure 3.2 above there are two heuristic functions given as an input to the phrase alignment model to be used as constraint rules while extracting and calculating model parameters. These two heuristic functions were designed to get better more reliable phrases.

The first heuristic was the source phrase to target phrase length ratio. Since the word, alignment model doesn't produce error free word alignments due to data sparseness problem. I added an upper and a lower bound to the phrase length ratio as an example it is obviously wrong to align a 4 word phrase with only one word phrase in the target and also we cannot align a 2 word phrase with 7 word long phrase in the target. This error happens usually due to data sparseness and behavior of the word alignment models in this case is to give a high fertility value for specific words and on the other hand aligns word with the NULL word. This can be shown in figure 3.5 below where we can see the word "punctuation" is aligned to four Arabic words.

The upper and the lower bound phrase length ratio is used during the phrase extraction step of the algorithm to qualify if this phrase should be added to the lexical model or not. As an example the heuristic function could be

$$|\tilde{e}| : |f'| >= 1:2 \text{ and } |f'| : |\tilde{e}| >= 1:2$$

$	1	0	0	0	0	0	0	0	0	0	0	0	0
the	0	0	0	0	0	0	0	0	0	0	0	0	0
most	0	0	0	0	0	0	0	0	0	0	0	0	0
comon	0	0	0	0	0	0	0	0	0	0	0	0	0
punctuation	0	1	1	0	1	1	0	0	0	0	0	0	0
marks	0	0	0	1	0	0	0	0	0	0	0	0	0
and	0	0	0	0	0	0	0	0	0	0	0	0	0
special	0	0	0	0	0	0	0	1	0	0	0	0	0
characters	0	0	0	0	0	0	1	0	0	0	0	0	0
are	0	0	0	0	0	0	0	0	0	0	0	0	0
available	0	0	0	0	0	0	0	0	0	0	0	0	0
under	0	0	0	0	0	0	0	0	0	0	0	0	0
the	0	0	0	0	0	0	0	0	0	0	0	0	0
number	0	0	0	0	0	0	0	0	0	0	0	1	0
key	0	0	0	0	0	0	0	0	0	0	1	0	0
.	0	0	0	0	0	0	0	0	0	0	0	0	1
	$	توفر	أكثر	علامات	الترقيم	شيوعًا	والحروف	الخاصة	على	مفتاح	الرقم	.	

Figure 3.5 : Wrong alignment example

The second heuristic function could be considered as adding linguistic knowledge to the phrase alignment model. It is related to the first word and the end word of the source or target phrase. As an example if we denote the first word in phrase ẽ or phrase ***f'*** as s1, depending on the direction of translation we are targeting, and the last word to be sn then

s1 <> ')' & '}' & '=' etc and sn <> '(' & '{' & '=' etc

could be considered as a constraint rule for qualifying whether to add this bilingual phrase to the phrase translation table. The main idea behind this constraint rule was to remove the noise found in the corpus.

3.3.4 Phrase Based decoder

The phrase-based decoder developed in the proposed system is different from Koehn et al [2003] which is discussed in chapter 2. The decoder developed by Koehn et al[2003] is based on the Bayes decision rule and source channel model while our decoder uses a direct approach in calculating p(e|f) as follows:

$$\mathbf{Pr(e|f) = argmax}\ (e'^{I}_{1}) \prod_{i=1\ to\ I} p(e'_i \mid f'_i) \qquad (1)$$

From the above equation we can conclude that our decoder is based on the assumption that the input sentence is segmented into a sequence of I foreign phrases. Each input phrase e'i or f'i ;depending on the direction of translation; is translated into an equivalent output phrase. So we assume a one to one phrase alignment. The main critical differences between our decoder and the one discussed in Koehn et al[2003] is

- No phrase reordering is needed while decoding.
- No n-gram language model used
- The decoder is using a direct approach in calculating Pr(e|f)

The main idea behind using the above assumptions was to use the divide and conquer approach in solving problems. If we divide the translation problem into three main sub-problems

1) Word translation choice
2) Local Word reordering within sentence segments
3) Sentence segments reordering

Then we can assume that our model will solve the first two problems by the phrase translation model discussed before and the remaining sub problem is also solved partially if the length of matching segments between the new sentence and the phrase

translation table is long enough. The third sub-problem, which is related to syntax difference between languages, could be tackled fully in a post-processing phase outside the scope of the decoder and this work.

These assumptions were used since we considered that the phrase based model learns explicitly the fertility, alignment and trigram-language models and we want to validate this in our model.

In summary, our assumption is that our phrase-based systems will learn lexical, distortion, fertility and language models better than the word based models due to the explicit learning of these models in our phrase translation model alone.

After this simplification to our decoder the maximization problem according to equation (1) above has been reduced to searching for the best segmentation of the sentence that produces the highest probability for Pr(e|f). We can compose this search problem as follows:

1) The decoder job is to extract all n-grams that appear in the test sentence up to a specific n according to the MaxPhraseLength used in the phrase translation model. As an example if the MaxPhraseLenght used is 5 then the decoder should extract all 5, 4, 3, 2 and unigrams found in the test sentence.
2) Then chooses the n-gram phrases that are not overlapping and produces the highest translation probability
3) Then for each of these n-grams the decoder should find the translation phrase with the highest probability from the Phrase translation table.
4) Finally, output the translated sentence after concatenating the translation phrase in the same order of the source phrases.

In figure, 3.6 below you can see the search tree for this problem. In this tree, we are assuming that the MaxPhraselength is 5. The nodes at depth 1 of the tree from left to right represents the first 5 , 4, 3, 2 and 1 gram phrases respectively. The nodes at depth 2 of the tree represent the next group of n-gram phrases following the parent phrase. While you go down the tree, you are consuming the test sentence from left to right.

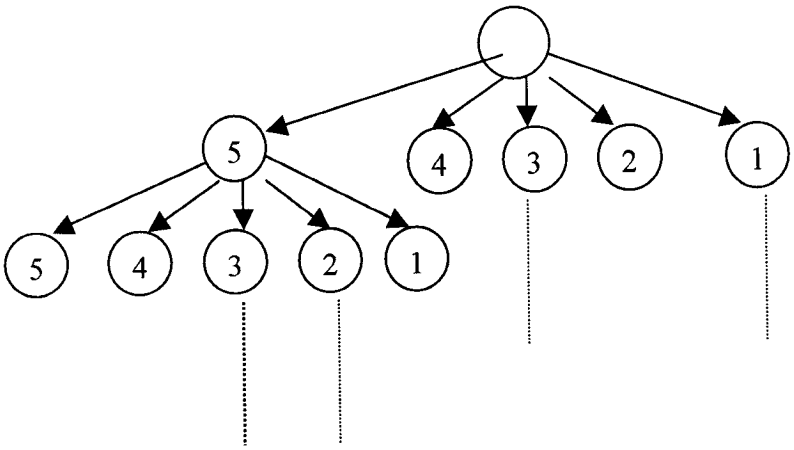


Figure 3.6: Search tree for traversing all possible n-grams in sentence

Our decoder traverses the tree using the depth first algorithm. This algorithm was chosen since we think that the best translation will be the one that segments the sentence into fewer segments with longer phrase length. Also we wanted to generate a list of possible translation sorted based on the value of Pr(e|f).

We can see that the search space for all possible translations is huge so we designed a heuristic function in order to prune the paths that are unlikely to lead us to one of the best translations according to the number of translation options required to be generated. This heuristic function was designed in order to make the decoding process computationally tractable.

```
Decode(TestString, ParentNode){

        For J = MaxPhraseLen Downto 1 {
                If (TestString > J) then { //If string length >

                  Curr_Phrase = Get_Phrase(TestString,J)

                  //Search in Translation Table & Return highest Prob. Phrase
                  GetTrans(CurrPhrase,Trans,Prob)

                  Node =New Node
                  Node->Length = J;
                  Node->Prob = Prob
                  Node->Trans = Trans

                  If (ParentNode != NULL) then
                        Node->AccLength = J+ ParentNode->AccLength;
                        Node->AccProb = Prob * ParentNode->AccProb
                  Else
                        Node->AccProb = Prob
                        Node->AccLen=J

                  //Get NewTest String afterremoving translated phrase

                  NewString = GetNewString(TestString,CurrPhrase)
                  AddChild(ParentNode,Node)

                  If(SolutionsCnt<=TotalNeeded)
                                    || (Node->AccProb)^1/n >=AvgProb)
                        If (NewString != NULL)
                              Decode(NewString,Node)
                        Else
                              //Back Track path to get full translation
                              Translation = GetTranslation(Node)

                              //Add Translation in N-bestlist Translation
                              //And update AvgProb
                              AddTrans(Translation,Node->AccProb)
                        Else
                              Do nothing (Prune Path)
                  } End If
        } //End For loop for children
}
```

Figure 3.7: Decoder Algorithm

The heuristic function was simply calculating the average word translation probability for the first path or the first "n" paths depending on the number of best results you want to generate then if the average word translation probability of the current path is lower than the n-best paths we backtrack and go to the next path.

The average word translation probability of the path is the $[Pr\ (e|f)]^{1/n}$ of the current path where n is the number of translated words up to this node.

Whenever we reach the end of a path if the probability Pr(e|f) is better than one of the n-best list we add this new translation and remove the one with lowest probability from the list and update the lowest average probability variable with the new probability.

In figure 3.7 we have given the algorithm of our decoder and in Appendix C of this thesis we can find the main classes and functions used in the development of this decoder.

We can say that our algorithm is a type of a Hill Climbing search where we get the first solution when traversing the tree in a depth first order then we try to find a better solution while continuing in the depth search but pruning the path that will unlikely lead us to a better solution. The advantage of our approach is that we can reach a solution very fast at the beginning of the search which also could be one of the best.

4 Experimentation

4.1 Evaluation Criteria

One of the debatable things in the machine translation community is how to evaluate system quality and results. Since a single sentence can have more than one correct translation and also since language in general also have what we call style of writing which differs from one person to another.

Since this thesis is interested in the area of computer aided translation field and how much can statistical machine translation increases productivity; I have chosen to use what is called the edit distance or the Levenshtein distance. The edit distance is a measure of the similarity between two strings, which we will refer to as the source string (s) and the target string (t). The distance is the number of deletions, insertions, or substitutions required to transform (s) into (t). For example, if (s) is "test" and (t) is "test", then LD(s,t) = 0, because no transformations are needed. The strings are already identical. If (s) is "test" and (t) is "tent", then LD(s,t) = 1, because one substitution is needed to transform (t) to (s) (change "n" to "s"). The greater the Levenshtein distance, the more different the strings are. I have normalized the output of this algorithm with regard to string length and got the percentage of similarity instead of the difference. so as to have a more clear value to be able to do the comparison on. You can find more explanation on the edit distance and its algorithm in: http://www.merriampark.com/ld.htm

This metric is used in all the CAT tools found in the market so this will make it easier for us to know how much SMT enhanced the CAT tool suggestion to the user.

4.2 Experiment 1: IBM Model 4 versus Phrase alignment model

4.2.1 Experiment Objective

This experiment was held to see how much our phrase-based model could enhance the outcome of the translation and to analyze why this is the case and how can we increase the quality of extracted phrases.

4.2.2 Experiment Details

Within this experiment we have executed several sub experiments on our extracted corpus. As it is stated in chapter 3 for the IBM word based models we used the GIZA++ toolkit together with the CMU language modeling toolkit and the ISI rewrite greedy decoder for the training and decoding of IBM model 4. While we used our internally developed phrase extraction tool together with our phrase based decoder for the training and decoding of the phrasal translation system.

In table 4.1 we can see the number of iterations used in the training of the word based machine translation.

Model	**Number of iterations**
Model 1	2
Model 2	5
Model 3	10
Model 4	15

Table 4.1: GIZA++ training iterations

IBM models training is based on the concept that each lower model is used to bootstrap the higher model i.e. instead of starting the training of a model with uniform parameters the parameters reached by the previous model training are used.

In all our experiments, we set the MaxPhraseLength to be 5 words. This decision was made based on the results obtained from similar experiments done [Koehn 2003] and showed that the enhancement in the quality of translation is minimal after phrase length of three.

We used the basic phrase alignment model generation tool without using any constraint regarding the source to target phrase length ratio. We just extracted the Phrase translation table based on the basic alignment file generated from the GIZA++ to be able to compare the basic phrase model with the word based models. However, in order to minimize the number of extracted phrases that will not be relevant in the translation phase we used the start word and end word constraint rule. We set this constraint to be as follows:

s1 <> ')' & '}' and sn <> '(' & '{'

see section 3.3.3 for more explanation.

The test sentences used in the experiments were extracted from the corpus using a tool that is included in GIZA toolkit. This toolkit extracts 3 per 1000 sentences making sure that these test sentences are not repeated in the training set.

Using the edit distance (Levenstien distance) metric we reached the results shown in table 4.2. Appendix D includes the translation of the 38 sentences of the Mobiles corpus in the English to Arabic direction.

Translation Direction	Corpus	# of test sentences	Model 4 average edit distance %	Phrase model average edit distance %
English to Arabic	Automotive	55	54.76	65.20
Arabic to English	Automotive	55	56.71	60.11
English to Arabic	Mobiles	38	47.20	77.87
Arabic to English	Mobiles	38	48.77	80.61
English to Arabic	Printers	49	43.50	47.37.
Arabic to English	Printers	49	45.99	50.32
English to Arabic	All	168	50.58	60.23
Arabic to English	All	168	47.75	60.65

Table 4.2: Experiment 1 results

4.2.3 Results analysis

From the experiment results above it can be shown that the quality of translation of the phrase-based model is superior compared with the word based IBM models 4. The minimum enhancement was approximately 3% while the maximum was approximately 32% which is quite a large gap. We can relate this large gap to the number of long phrases matched with the test sentences (i.e phrases of length 3 or more matching with the phrasal lexicon) see figure 4.1. The word based models didn't make use of that since the translation is dependent on using word for word replacement.

By closely analyzing the output from both models, we can reach the following conclusions:

1. The word reordering problem is better modeled by the inclusion of this information in the phrase translation table directly. This can be shown in the following translation example taken from the output of this experiment:

Source : fuel tank
HumanTranslation: خزان الوقود
Our Translation: خزان الوقود
Model 4 Translation: الوقود خزان

We can relate this problem to the size of the corpus used in the training.

2. Although our decoder always chooses the target phrase based only on the translation probability table calculated by the phrase translation model and ignores totally the language model effect; still our phrase decoder generates better translation syntactically and semantically than the word based decoder which uses a tri-gram language model. So we can say that our assumption that the language model is explicitly learned within the Phrase translation table is to a large extent correct except when we get a test sentence that most parts of it matches phrases of length 2 or less words. In this case also word based systems generates translation that is not useful in our goal application which is technical translation domain.

Example1:

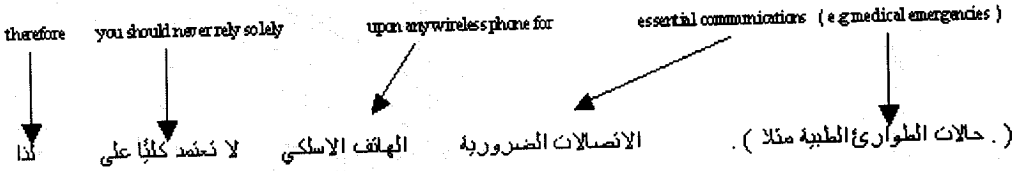
Source Sentence: therefore you should never rely solely upon any wireles phone for esential comunications (e.g medical emergencies)

Target Sentence: . (لذا لا تعتمد كلياً على الهاتف الاسلكي في الاتصالات الضرورية (حالات الطوارئ الطبية مثلا

Phrase based Translation: لذا لا تعتمد كلياً على الهاتف الاسلكي الاتصالات الضرورية (حالات الطوارئ الطبية مثلا) .

Model 4 Translation: لذا الذي ينبغي أبدًا الضرورية الضرورية تحده أي الاسلكية الهاتف لمدة مطلقًا اتصالات (e . g . المعدات مثلا) .

Phrase based Alignment:



Example2:

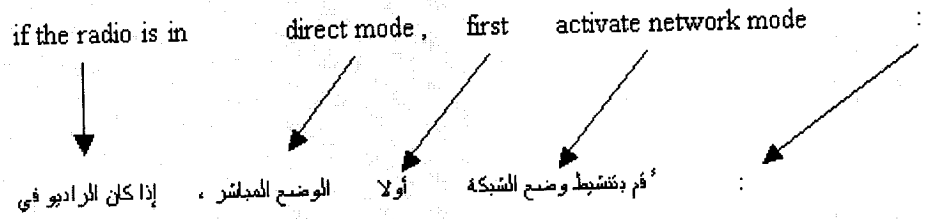
Source Sentence: if the radio is in direct mode , first activate network mode :

Target Translation: : إذا كان الراديو في الوضع المباشر ، قم أولاً بتنشيط وضع الشبكة

Phrase based Translation: : إذا كان الراديو في الوضع المباشر ، أولاً قم بتنشيط وضع الشبكة

Model 4 Translation: إذا الراديو في المباشر وضع ، أولاً قم الشبكة وضع

Phrase based Alignment:



Example3 :

Source Sentence: the blinking continues for aproximately 10 minutes or until the headset is connected to a compatible phone

Target Translation: قد يستمر الوميض لمدة ١٠ دقائق تقريبًا ، أو حتى يتم توصيل سماعة الرأس بهاتف متوافق ، أيهما أقرب .

Phrase based Translation: . الوامبض يستمر لمدة ١٠ دقائق تقريبًا ، أو حتى يتم توصيل سماعة الرأس إلى هاتف متوافق

Model 4 Translation: . الوميض يستمر لمدة تقريبًا ١٠ دقائق أو حتى الرأس توصيل إلى متوافق الهاتف :

Phrase based Alignment:

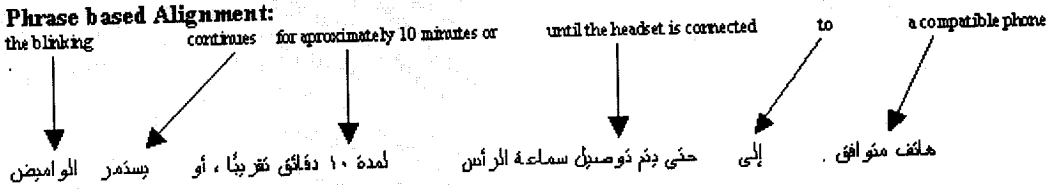


Figure 4.1: Translation examples from experiment 1

3. In our phrase based decoder, we didn't use the distortion and fertility tables learned by the IBM model 4. We depended that our phrase based translation model implicitly learned that while extracting the phrases even in phrases of length 1. After analyzing the outcome from both models we found that our decoder generates better

translation than the word based decoder so this means that the fertility and distortion models in the phrase based decoding could be ignored without affecting the final outcome of translation when compared with word based decoding.

4. We have discovered that some of the errors in the outcome of our decoder were due to wrong word alignment coming from the word based alignment models. One of the problems with the alignment generated by word based models is due to data sparseness. For example if a rare word occurred in a sentence this sentence will end up with wrongly NULL aligned words and increasing the fertility of other words. This was shown previously in figure 3.5 where the word "punctuation" is aligned with 4 arabic words while "the", "most" and "common" are aligned with NULL.

4.3 Experiment 2: Phrase based alignment heuristics

4.3.1 Experiment Objectives

In experiment 1 results analysis we have shown that some of the errors generated by our decoder was dependent on the wrong word alignment generated by word based alignment models. We need to experiment if by using our suggested source phrase to target phrase length ratio heuristic can we enhance the quality of translation. Also will the heuristics suggested by Och et. Al [1999] and explained in chapter 3 of this thesis enhance the quality of the proposed system output.

4.3.2 Experiment details

In this experiment, the automotive and Mobiles corpuses were used. As experiment 1 the MaxPhraseLength was 5. We have run a total of 12 experiments. For each translation direction (i.e. English to Arabic or Arabic to English) using the

mobile corpus we ran 3 experiments and the same 3 experiments was done using the automotive corpus.

Translation Direction	Corpus	test sentences #	Phrase model edit distance %	Phrase Length ratio edit distance %	AndOr model edit distance %	AndOr length ratio edit distance %
En to Ar	Auto	55	65.20	64.13	65.83	65.86
Ar to En	Auto	55	60.11	60.05	59.78	59.67
En to Ar	Mobiles	38	77.87	77.43	76.96	77.03
Ar to En	Mobiles	38	80.61	80.12	79.94	79.97

Table 4.3: Experiment 2 results

In the first experiment, which we named "Phrase Length ratio" in table 4.3, we used the constraint rule source phrase to target phrase length ratio parameter to be

$$|\tilde{e}| : |f'| >= 1:2 \text{ and } |f'| : |\tilde{e}| >= 1:3 \qquad (3)$$

The second experiment, which we named "AndOr model" in table 4.3, uses Och heuristics in building the word alignment matrix. Finally the third experiment named "AndOr length constraint" is a combination of both i.e. we used Och heuristics in building the word alignment matrix and when generating the phrase alignment matrix we used the same constraint rule in equation (3). You can view the edit distance results of the 12 experiments compared with the basic phrase model in table 4.3.

4.3.3 Results Analysis

We found that the Andor heuristic didn't enhance the quality of translation over the basic phrase extraction technique. However, some experiments yielded a

lower quality from the edit distance metric point of view. Also was the case with the phrase length constraint.

So we can say that these heuristics will not enhance the translation quality of the system in the application this thesis is interested in. Since the human translator will be interested in getting translation suggestions that needs the minimal addition or deletion or substitution operations (edit distance) to reach the desired correct translation.

From the previous results, we can see that these heuristics didn't affect the translation quality in a negative way to the extent that the translator can feel any difference. On the other hand, since the source to target phrase length ratio could be considered as a constraint rule that will decrease the number of possible phrases to be

Translation Direction	Corpus	Phrase model	Phrase Length constraint	Difference in %
En to Ar	Mobiles	185777	170309	9.6%
Ar to En	Mobiles	199998	184215	8.1%
En to Ar	Auto	338668	300424	12.7
Ar to En	Auto	362958	323502	11.1%

Figure 4.4: Number of phrases extracted comparison

extracted then if we used this heuristic it will decrease the amount of memory used by our decoder. This conclusion could be seen from table 4.4 above. The results shown are for the phrases extracted from the Mobiles and the automotive corpuses once using the basic phrase translation table generation algorithm and the other after adding the source to target phrase length ratio. It is clear from the last column that the

minimum decrease in size of the phrase translation table is 8.1% and this will lead to less memory used by the decoder.

4.4 Experiment 3: CAT tool versus SMT suggestions

4.4.1 Experiment Objectives

Since one of the main goals of this thesis is to proof that by integrating statistical machine translation system with the commercial CAT tools we can get better fuzzy match suggestions and this will lead to increasing the productivity of the human translator in the technical domain translation industry. So to proof that; an experiment was done in order to compare the fuzzy match suggested by the translation memory and the translations generated by our phrase based decoder.

4.4.2 Experiment details

The test was extracted from a new mobile phone manual. The CAT tool used in this experiment is Trados one of the industry leaders. The TM used was the same corpus our machine translation was trained on. The first 13 sentences in the manual where extracted together with the suggestions generated by the CAT tool. You will find below in table 4.5 the suggestions generated by the TM with the percentage of fuzzy match.

Source	TM Suggestion	Fuzzy match
Open Addressbook (in standby mode)	$ المؤشرات الأساسيه في وضع الانتظار	44%
Display input fields		0%
At least one name must be entered.	$ يحتوي أحدهما على الأقل على بيانات صالحة .	38%
Always enter phone number with prefix.	$ الرجاء إدخال رقم.	44%
Allocation to a group	$ لتحديد مجموعة:	58%
After activation, you can enter the date of birth.	$يمكنك الاطلاع على ملخص لإجراء أدنا .	45%
Assign a picture to the entry.	$ قم بإجراء مكالمة إلى المشارك الأول .	45%
Save the entry.	حفظ ملف	49%
Additional information	حذف المعلومات	38%
Display options	خيارات	50%
Change entry	إضافة إدخال	34%
Read entry	إدخال جديد	50%

The number is dialled.	$ معاودة الاتصال بآخر رقم تم الاتصال به	50%

Table 4.5: TM fuzzy match

The same test sample was translated using our phrase based decoder to be able to compare the suggested fuzzy match translations with our translation and see how much the human translator will benefit from these translations.

Human Translation	Machine translation	Edit distance
لفتح دليل العناوين (في وضع الانتظار)	فتح adresbok (في وضع الانتظار)	63.15
لعرض حقول الإدخال	الشاشة لنص الحقول	23.52
يجب إدخال اسم واحد على الأقل.	واحدة على الأقل اسم تكون لتو .	20
أدخل رقم الهاتف متضمنًا البادئة دومًا.	دومًا أدخل رقم الهاتف مع البادئة .	55.26
للتخصيص لمجموعة	تخصيص قناة راديو إلى إحدى المجموعات) alocation	25.53
بعد التنشيط؛ يمكنك إدخال تاريخ الميلاد	بعد تشغيل ، يمكنك أدخل تاريخ الميلاد .	71.05
لتخصيص صورة للإدخال.	خصص صورة إلى إدخال .	65
لحفظ الإدخال.	حفظ الإدخال .	92.85
معلومات إضافية	معلومات إضافية	100
خيارات العرض	خيارات العرض	100
تغيير إدخال	تغيير إدخال	100
قراءة الإدخال	اقرأ إدخال	53.84
يتم الاتصال بالرقم.	الرقم الصادرة .	31.57

Table 4.6: Edit distance between SMT & Human translation

Table 4.6 is showing the translation output of our decoder compared with the human translation for the same set of test sentences above. The last column is the edit distance between the human translation and the machine translation. In table 4.7 you can find the edit distance between the human translation and the CAT tool suggestions.

Human Translation	TM suggestions	Edit distance
لفتح دليل العناوين (في وضع الانتظار)	$ المؤشرات الأساسيه في وضع الانتظار	55.55
لعرض حقول الإدخال		0
يجب إدخال اسم واحد على الأقل.	$ يحتوي أحدهما على الأقل على بيانات صالحة .	29.54
أدخل رقم الهاتف متضمنًا البادئة دومًا.	$ الرجاء إدخال رقم.	21.05
للتخصيص لمجموعة	$ لتحديد مجموعة:	52.947
بعد التنشيط؛ يمكنك إدخال تاريخ الميلاد	$يمكنك الاطلاع على ملخص لإجراء أدنا .	13.15
لتخصيص صورة للإدخال.	$ قم بإجراء مكالمة إلى المشارك الأول .	20.51
لحفظ الإدخال.	حفظ ملف	38.46
معلومات إضافية	حذف المعلومات	7.142
خيارات العرض	خيارات	50
تغيير إدخال	إضافة إدخال	54.54
قراءة الإدخال	إدخال جديد	15.384
يتم الاتصال بالرقم.	$ معاودة الاتصال بآخر رقم تم الاتصال به	35.89

Table 4.7: TM suggestions versus human translation output

4.4.3 Results Analysis

From the experiment we can conclude that the translation outcome of our decoder was in almost all the sentences better and closer to the correct translation than what was suggested by the CAT tool. In addition, even when the CAT tool was better from the point of view of the edit distance metric it is still not usable by the translator except in one sentence. We did a survey with three experienced technical translators and we supplied them with both results we found out that translators will not make use of any suggestion that will be below 50 %. From table 4.8 you will find that according to this the translators will make use of 9 suggestions from our decoder while only one suggestion will be used from the TM.

CAT Edit distance	MT Edit distance	Useful translations
55.55	63.15	MT
0	23.52	NONE
29.54	20	NONE
21.05	55.26	MT
52.947	25.53	CAT
13.15	71.05	MT
20.51	65	MT
38.46	92.85	MT
7.142	100	MT
50	100	MT
54.54	100	MT
15.384	53.84	MT
35.89	31.57	NONE

Table 4.8: CAT Vs. MT Useful suggestion

From this conclusion we can suggest an architecture for an enhanced CAT environment that would increase the productivity of the translator by supplying him

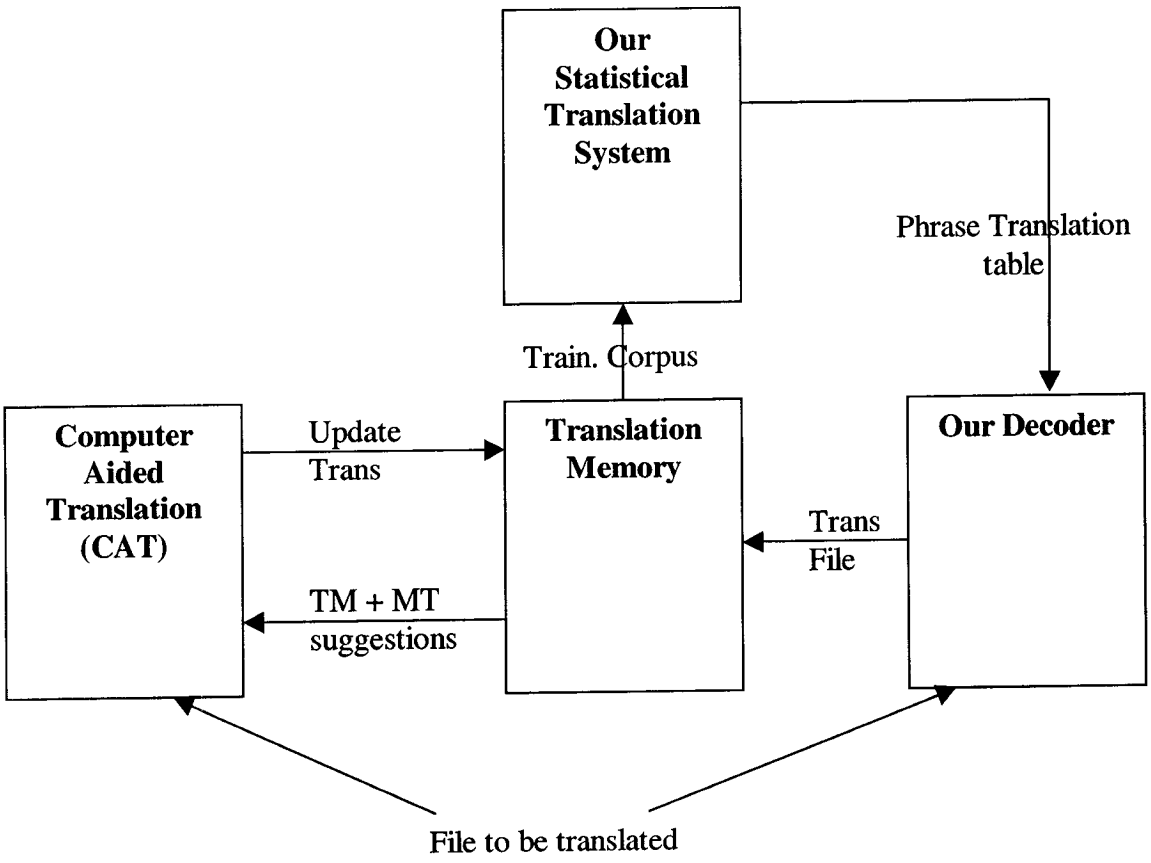


Figure 4.2: SMT within CAT framework

with more accurate translation suggestions that would minimize the work needed in translating a technical document.

This architecture is shown in figure 4.3 above. After training our phrase based translation model using the corpus supplied from the TM if we have a new file supplied for translation then we first translate this file using our decoder and update the TM with the translation of the new file based on our decoder. The second stage is to supply the file to the CAT tool to be translated with a human translator. The TM will now supply the suggestion for all sentences based on the output of our decoder. If the human translator does any changes, the TM will be automatically updated with these changes. After the file is translated, we will have a new corpus which includes all new translated sentences. We can now train our model again with this new corpus and this will lead to a system that will get better over the time.

5. Conclusion

We have developed a phrase based statistical translation system. In this system we build phrase based translation model and a decoder that works with it. Our decoder simplified the translation problem based on the assumption that there is no difference in order between phrases in the target and source languages and accordingly didn't use any language model nor distortion model within the search for the translation.

We have shown that by using the translations generated by this system instead of the TM suggestions, the translator will get better suggestions and thus increase his productivity. Then we presented an architecture showing how we can include our SMT system within the framework of CAT. In this new CAT environment, we replace the TM suggestion module by our SMT system.

In addition, we have shown in our experimentations that although the corpus size was less than 20,000 sentences in certain experiments as the mobile corpus the proposed system was able to learn word reordering better than the word based models.

Moreover, we have found that by adding a simple heuristic; which limits the bilingual phrases to be extracted from the corpus based on the source and target phrase length ratio; that was suggested in this work we could decrease the size of the phrase translation table. This will make our decoder more effective from the point of view of memory usage and at the same time will not affect the quality of the translation to a noticeable percentage

Finally, we were able to explore all the questions that was set as objectives for this thesis and stated in chapter 1. However, we still have the following topics remaining for future work. After analyzing the output and from the architecture of the proposed system it could be shown that the proposed system lacks information needed to generate syntactically accurate output. Although we have shown that our model

learns local word reordering within the sentence better than the word based SMT it remains a question how to model global word reordering within the sentence.

One idea is to add a new module as a syntax language model and experiment the proposed system with this module. This will need from us first to have an annotated Arabic corpus in order to be able to train the syntax language model then do experiments by including this module as a pre processing unit that when given a sentence it generates the same sentence but ordered according to the target language syntax. Also try the same module but after including it within the maximization problem of the decoder i.e. including it in the equation that the decoder is trying to maximize.

Other idea is to add a preprocessing module that performs morphological analysis in order to enhance the quality of the word alignment generated by word based models.

Finally, instead of using a statistical distortion and language model we can use an English-Arabic rule based syntax analyzer that will parse the English sentence and reorders the sentence according to the correct Arabic parse tree then apply our decoder on the converted sentence.

In conclusion, we want to add to the proposed system syntax knowledge about the source and target languages in order to go higher in the Vauquois triangle as shown in figure 1.1.

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Appendix A

Part of Phrase translation table from English to Arabic alignment

Source Phrase	Target Aligned Phrase	P(f'|e')	Frequency
automaticaly starts a slide show	يبدأ عرض الشرائح تلقائيًا بمجرد	1	1
automaticaly switches on the transmitter	تشغيل جهاز الإرسال تلقائيًا	1	1
automaticaly switching the transmitter of	تشغيل جهاز الإرسال تلقائيًا	1	1
automaticaly tagstarts playing the file	تلقائيًا tagيبدأ قراءة الملف بمجرد	1	1
automaticaly update the time and	لتحديث الوقت	1	1
automaticaly with any of the	تلقائيًا مع أي	1	1
availability , performance , utilization	تعلق التوافر والأداء والانتفاع والحالة	1	1
availability , rates and information	لمعرفة مدى توافر	1	1
availability and a subscription to	لحصول على معلومات حول إمكانية الاشتراك	1	1
availability and the synchronisation service	مدى توفر خدمة التزامن وضبطها	1	1
availability may vary by country	قد يرتبط توفر ذلك حسب الدولة	1	1
availability of an operator logo	مدى توفر شعار الشبكة	1	1
availability of aproved accesories ,	لحصول على قائمة بالمستلزمات المعتمدة ،	1	1
availability of aproved batteries and	لحصول على بطاريات وأجهزة	1	1
availability of aproved chargers ,	لحصول على أجهزة شحن معتمدة ؛	1	1
availability of diferent wap services	لمعرفة مدى توافر خدمات wap المختلفة	1	1
availability of particular products may	يختلف توفر منتجات معينة	1	1
availability of the settings ,	توافر هذا الضبط ،	1	1
availability of wap services ,	توافر خدمات wap ،	0.5	1
availability of wap services ,	مدى توفر خدمات wap	0.5	1
available , for example ,	متوفرًا مثلا	1	1
available folders in the #	الحافظات المتوفرة في	1	1
available for a game or	المتوفرة لعبة أو	1	1
available for an aplication or	المتوفرة لتطبيق أو	1	2
available for control signaling in	يتوفر بها	1	1
available for control signaling when	التحكم	1	1
available for diferent phone models	المتوفرة لطرازات الهواتف المختلفة	1	1
available for download from the	من	1	1
available for the divert option	متوفرًا في خيار التحويل	1	1
available for the languages in	لغات الموجودة	1	2
available for the phone .	بالهاتف .	1	1
available for your phone .	.	1	1
available functions is shown .	المتاحة .	1	1
available in http : /	: http : /	1	1
available in this window ,	المتوفرة في هذا الإطار ،	1	1
available memory depends on the	الذاكرة المتوفرة على	1	1
available on the mobile device	المتاحة على الهاتف المحمول	1	1
available on your sim card	متاحة على بطاقة sim لديك	1	1
available to complete synchronization !	لإتمام التزامن !	1	1
available topics and the relevant	المعلومات حول الموضوعات المتوفرة	1	1
available under each key are	المتوفرة على كل مفتاح	1	1
available while a wap connection	عند تشغيل wap	1	1

averaged over ten grams of	بالمعدل لعشرة	1	1
avoid potential interference with the	والجهاز	1	1
avoid similar names for diferent	وتجنب استخدام الأسماء المتشابهة لأرقام المختلفة	1	1
avoid the ned to queue	وتجنب الانتظار حتى يأتي	0.5	1
avoid the ned to queue	وتجنب الحاجة إلى الانتظار حتى يأتي	0.5	1
avoid using acces codes similar	تجنب استخدام رموز الوصول المشابهة لأرقام	1	1
away from smal children .	بعيدًا عن متناول الأطفال الصغار .	1	1
away from the camera to	بعيدًا عن الكاميرا	1	1
away from the face and	بعيدًا عن الوجه	1	1
away from the mouth with	من الفم تقريبًا بحيث يتجه	1	1
away from your face and	بعيدًا عن الوجه	1	1
away from your mouth with	من الفم تقريبًا بحيث يتجه	1	1
b , or c)	b أو c)	1	1
b . ad text :	ب . إضافة (نص) (:) text	0.5	1
b . ad text :	ب . إضافة (نص) : text	0.5	1
b . click on the	ب . انقر فوق	1	2
b . to select part	ب . لتحديد جزء	1	2
b and c) on	b وc)	1	2
b or c) of	b أو c)	1	1
back - up data from	احتياطية منها	1	1
back #/ dt # .	" .	1	1
back #/ dt # and	"	1	1
back #/ dt # or	" أو	1	1
back #/ dt # to	"	1	3
back and downwards so that	حتى	1	1
back and pres (graphic	به ثم اضغط على #	1	1
back cover of the phone	الغطاء الخلفي لهاتف	0.25	1
back cover of the phone	غطاء الهاتف الخلفي	0.5	2
back cover of the phone	غطاء الهاتف الخلفي بعيدًا عن الهاتف	0.25	1
back cover so that the	الغطاء الخلفي	1	1
back from privacy mode to	من وضع الخصوصية إلى	1	1
back key in direct mode	التراجع في الوضع المباشر	1	1
back key in the midle	مفتاح التراجع الموجود في وسط	1	1
back key selects the first	مفتاح التراجع إلى تحديد أول	1	1
back key switches betwen the	ذات المفتاح إلى الانتقال بين	0.25	1
back key switches betwen the	مفتاح التراجع إلى الانتقال بين	0.25	1
back key switches betwen the	مفتاح التراجع إلى التنقل بين	0.5	2
back of the nokia image	الخلفي	1	1
back of the phone ,	الهاتف ،	1	1
back of your computer and	مؤخرة الكمبيوتر	1	1
back of your pc .	خلف الكمبيوتر .	1	1
back on by presing any	بالضغط على أي	1	1
back the settings to the	إرسال الإعدادات إلى	1	1
back to arabic text input	لعودة إلى وضع إدخال الغة العربية	1	1
back to go to the	السابق لعودة إلى	1	1
back to return to the	السابق لعودة إلى	1	2
back to the homepage of	الصفحة الرئيسية الخاصة	1	1
back to the previous ones	إلى وضعه السابق	1	1

back to the previous page	إلى الصفحة السابقة	1	1
back to the suport pages	إلى صفحات الدعم	1	2
back up data on your	حفظ نسخة احتياطية من البيانات الموجودة	1	1
back up information on a	عمل نسخ احتياطية من المعلومات المسجلة	0.5	1
back up information on a	وعمل نسخة احتياطية من المعلومات الموجودة	0.5	1
background and a non -	بينما تظل	1	1
background folder #/ dt #	حافظة الخلفية "	1	1
background groups are used for	تستخدم المجموعات	1	1
background groups in scanning)	والمجموعات الخلفية ضمن عملية المسح (	1	1
background image , known as	صورة خلفية تعرف	1	1
background images in the phone	خلفية في الهاتف	1	1
background lights changes randomly .	الأضواء الخلفية بطريقة عشوائية .	1	1
background picture , walpaper ,	صورة خلفية أو ورق حائط	1	1
background when performing other operations	الخلفية أثناء أداء عمليات أخرى	1	1
backslash (\ ) acros	شرطة مائلة (\ ) على	0.5	1
backslash (\ ) acros	وضع شرطة مائلة (\ ) على	0.5	1
backup copies of al important	عمل نسخ احتياطية من جميع	0.5	1
backup copies of al important	نسخ احتياطية من جميع	0.5	1
backup copies of your images	عمل نسخ احتياطية من الصور الخاصة	1	1
backwards (4) and	لخلف (٤)	1	1
backwards , pres (graphic	لخلف ، اضغط على (graphic	1	1
backwards and down or up	أو	1	1
bag , remember that an	الواقية ، تذكر أن	1	1
bag inflates , serious injury	الوسادة ، ربما ينجم عن ذلك إصابة خطيرة	1	2
bag inflates with great force	الوسادة تفتح بقوة شديدة	1	1
balance settings to get the	موازنة الون الأبيض لوصول إلى	1	1
bank account) , empty	البنك) ، فقم بتفريغ	1	1
banking , news , weather	الخدمات المصرفية والأخبار	1	1
banking services , and for	الخدمات المصرفية	1	1
banking services , you ned	الخدمات البنكية ، التي تحتاج	1	1
banking services or shoping on	الخدمات المصرفية أو التسوق من خلال أحد مواقع	1	1
bar (1) .	(1) .	1	1
bar (1) and	-1	1	1
bar , the more power	دل ذلك على كثرة الطاقة	1	1
bar , the stronger the	، دل على قوة	1	1
bar above (graphic)	الشريط الموجود أعلى ((graphic	1	1
bar is shown on the	عرض الشريط على	1	1
baring pasword (4 digits	كلمة سر الحظر (٤ أرقام	1	1
baring pasword is neded when	يلزم إدخال كلمة سر الحظر عند	1	1
baring pasword is required .	يلزم إدخال كلمة سر الحظر .	1	1
baring service #/ dt #	"	1	1
baring service #/ dt #,	سر الحظر	1	1
bars of nokia pc suite	شريط المعلومات الخاص بتطبيقات nokia pc suite	1	1
base station (bs)	base station (المحطة الأساسية) : bs	1	1
base station (radio unit	محطة رئيسية (وحدة راديو	1	1
base station (s)	المحطات الرئيسية	1	1

Appendix B

Phrase Alignment Generation Source Code
Main Classes Definition

```
//---------------------------------------------------------------------------
// Main Classes
#ifndef LexH
#define LexH
#include <StrUtils.hpp>
#include <sysdyn.h>
#include <stdio.h>
#include <io.h>
#include <alloc.h>
#include <fcntl.h>
#include <process.h>
#include <sys\stat.h>
#include <Classes.hpp>
#include <StdCtrls.hpp>
#include "Matrix.h"
//---------------------------------------------------------------------------
/*
Tlex class is reponsble for analyzing single matrix
and getting all valid Bilingual Phrases of specific Phrase Length

*/

class TLex
{
private:
        int LexLen;//Phrase Length
        int MinimumRation;
        int MaximumRation;
        String Stdelimt;
        String Enddelimt;
        TMatrix *Matrix;//Matrix object to be converted to lexicon item
        TStringList *Sourcelst;//List of Src words index
        TStringList *Targetlst;//List of trgt words index
        TStringList *SemiLexlst;//Memory Phrase table
        TStringList *Stdelimtlst;
        TStringList *Enddelimtlst;
        int targetFirst;
        int MaxIndex,MinIndex;// min. and max. numbers
                        // used to get the NULL aligned words

        //function used to add leading zeros to an integer e.g. 1 become "001"
```

```
        String str(int i);

        //function used to check if valid phrase to add it to Mem. Phrase Table
        int ValidPhrase();

        // returns a string before a specific delimiter
        String GetDelimit(String* StrSource,String Delimit);

public:
        TLex(int Length,TMatrix *Mx,TStringList *SLexlst,int MinRation,
                String SD,String ED,int Tgtfirst,int MaxRation);
        ~TLex();


        void GetLexItems();
        void GetLexItem(int Index);
        void GetLexItemsInBetween();
        void WriteItem();//writes items to Mem. Phrase table
        void Fill_delimit_list();

};
//---------------------------------------------------------------------------
#endif
```

Main Classes Implementation

```
//---------------------------------------------------------------------------


#pragma hdrstop
#include "Lex.h"


//---------------------------------------------------------------------------
TLex::TLex(int Length,          //SrcPhraseLen
        TMatrix *Mx,            //Word aligned Matrix
        TStringList *SLexlst,   //Memory Phrase Table
        int MinRation,          // Min SrcToTrgt phrase Ratio
        String SD,String ED,    //Start And end Delimiters
        int Tgtfirst,           //Not used
        int MaxRation)   // Min SrcToTrgt phrase Ratio
 {
        LexLen=Length;
        Matrix=Mx;
        Targetlst=new TStringList;
        Sourcelst=new TStringList;
        SemiLexlst= SLexlst;
        MinimumRation=MinRation;
        MaximumRation=MaxRation;
```

```
        Stdelimt=SD+",";
        Enddelimt=ED+",";
        Stdelimtlst=new TStringList;
        Enddelimtlst=new TStringList;
        Fill_delimit_list();
        targetFirst=Tgtfirst;

}
//---------------------------------------------------------------------
TLex::~TLex()
{
        delete Sourcelst;
        delete Targetlst;
        delete Stdelimtlst;
        delete Enddelimtlst;
}
//---------------------------------------------------------------------
void TLex::GetLexItems()
{
        // a loop to get all source segments combination to be added to phrase
        //table
        for (int i =0;i<Matrix->xlen-LexLen+1;i++)
        {
                //clear lists
                Sourcelst->Clear();
                Targetlst->Clear();
                // initmax and min indexes
                MaxIndex=-1;
                MinIndex=-1;
                // a loop to add source words and its aligned targets
                for (int j=0;j<LexLen ;j++)
                {
                        // add source word
                        Sourcelst->Add(str(i+j));
                        // call function to get aligned words
                        GetLexItem(i+j);
                }
                //check if there is null aligned words in between
                if(MinIndex>-1)
                        GetLexItemsInBetween();
                //check if target phrase is cont.
                if (ValidPhrase())
                        //add item to memory phrase table
                        WriteItem();
        }
}


//---------------------------------------------------------------------
```

```
// get aligned target words for a specific source word

void TLex::GetLexItem(int Index //index of source word
                      )
{
     for (int j=0;j<Matrix->ylen ;j++)
     {
          if (Matrix->Data[Index][j]=="1")
          {
               if (Targetlst->IndexOf(str(j))==-1)
               {
                    //add target word index to target list
                    Targetlst->Add(str(j));
                    //reset min and max indexes
                    if (j>MaxIndex)
                         MaxIndex=j;
                    if (j<MinIndex||MinIndex==-1)
                         MinIndex=j;
               }
          }
     }
}

//---------------------------------------------------------------------------
// get all nul aligned words between min and max index
void TLex::GetLexItemsInBetween()
{
     for (int i=MinIndex+1;i<MaxIndex;i++)
     {
          int Assigned=0;
          for (int j=0;j<Matrix->xlen;j++)
          {
               if (Matrix->Data[j][i]=="1")
                    Assigned=1;
          }
          if (Assigned==0)
               Targetlst->Add(str(i));
     }
}
//---------------------------------------------------------------------------
// write sorce and target segments to phrase table memory
void TLex::WriteItem()
{
     Sourcelst->Sort();
     Targetlst->Sort();
     String Line;
     String srcline=Matrix->Source[Sourcelst->Strings[0].ToInt()];
     for (int i=1;i<(Sourcelst->Count);i++)
     {
```

```
        srcline+=" "+Matrix->Source[Sourcelst->Strings[i].ToInt()];
    }

    String tgtline;
    if (Targetlst->Count >0)
        tgtline=Matrix->Target[Targetlst->Strings[0].ToInt()];

    for (int j=1;j<(Targetlst->Count);j++)
    {
        tgtline+=" "+Matrix->Target[Targetlst->Strings[j].ToInt()];
    }
    if (targetFirst==1)
        Line= tgtline+"\t"+srcline;
    else
        Line= srcline+"\t"+tgtline;

    SemiLexlst->Add(Line);

}
//---------------------------------------------------------------------------
//check if phrase is valid
int TLex::ValidPhrase()
{
    int res=1;
    // if it has no translation then it is not valid
    if (Targetlst->Count==0)
        return 0;
    // if target to source ratio length is less than min ratio then it is
    // not valid
    if ((1.00*Targetlst->Count/Sourcelst->Count)<(1.00*MinimumRation/100))
        return 0;
    // if target to source ratio length exceeded max ratio
    //then it is not valid
    if ((1.00*Targetlst->Count/Sourcelst->Count)>(1.00*MaximumRation/100))
        return 0;
    // if segment starts with a linguisticall not correct word
    //then it is not valid
    if (Stdelimtlst->IndexOf
        ((Matrix->Source [Sourcelst->Strings[0].ToInt()])[1] )!=-1)
        return 0;
    // if segment ends with a linguisticall not correct word
    // then it is not valid
    if (Enddelimtlst->IndexOf((Matrix->Source[Sourcelst->Strings
                    [Sourcelst->Count-1].ToInt()])[1])!=-1)
        return 0;
    //check on continuity
    for (int i=MinIndex+1;i<MaxIndex;i++)
    {
        if (Targetlst->IndexOf(str(i))==-1)
```

```
                res=0;
        }
        return res;


}
//---------------------------------------------------------------------------
String TLex::str(int i)
{
        String res;
        if (i >99)
                res=IntToStr(i);
        else if (i >9)
                res="0"+IntToStr(i);
        else
                res="00"+IntToStr(i);

        return res;
}
//---------------------------------------------------------------------------
void TLex::Fill_delimit_list()
{
        while (Stdelimt!="")
        {
                Stdelimtlst->Add(GetDelimit(&Stdelimt,","));
        }
        while (Enddelimt!="")
        {
                Enddelimtlst->Add(GetDelimit(&Enddelimt,","));
        }

}
//---------------------------------------------------------------------------
String TLex::GetDelimit(String* StrSource,String Delimit)
{
        String result=MidStr(*StrSource,0, StrSource->AnsiPos(Delimit)-1);
        *StrSource=MidStr(*StrSource,
            StrSource->AnsiPos(Delimit)+Delimit.Length(),StrSource->Length());
        return (result);
}
//---------------------------------------------------------------------------

void TMatrices::GetMatrices_To_Lex(
                        String SLex_file,
                        String Lex_file,
                        int Sourcecnt,
                        int MinRation,
                        String SD,String ED,
                        int Tgtfirst,int MaxRation)
```

```
{
  TStringList *LexlstPart=new TStringList ;//a temp. phrase table
                              //to be filled with one matrix
                              //bilingual phrases

  TStringList *SLexlst=new TStringList ;// memory phrase table

  TStringList *Lexlst=new TStringList ;// Phrase table

  int MatrixNum=Readfromlist(Datalines);
  for (int I = 0 to MatrixNum)
  {
       TLex *Lex=new TLex(Sourcecnt,Matrix[I],LexlstPart,
                    MinRation,SD,ED,Tgtfirst,MaxRation);
       Lex->GetLexItems();
       delete Lex;
       //add current temp memory phrase table to full memory phrase
       SLexlst->AddStrings(LexlstPart);

       LexlstPart->Clear();//clear temp for new sentence
  }
  SLexlst->Sort();//Sort Memory Phrase Table to get probabilities
  Compute_Phrase_prob(SLexlst,Lexlst);
  Lexlst->SaveToFile(Lex_file);
  delete  SLexlst;
  delete  Lexlst;


}

//---------------------------------------------------------------------------


#pragma package(smart_init)
```

Appendix C

Decoder Main Source Code

Main Classes Definition

```
//---------------------------------------------------------------------------

#ifndef testH
#define testH
#include <StrUtils.hpp>
#include <sysdyn.h>
#include <stdio.h>
#include <io.h>
#include <alloc.h>
#include <fcntl.h>
#include <process.h>
#include <sys\stat.h>
#include <Classes.hpp>
#include <StdCtrls.hpp>
#include <StrUtils.hpp>
#include "Lex.h"
#include <ComCtrls.hpp>


// NodeDataStruct is A Structure to store every segment node data in
// the search tree

typedef struct NodeDataStruct
{
 String Translation;    //stores segment translation
 float Probability;     //stores segment probability
 float AcumProbability; //stores Accumulated segments probability in the path
 int Length;            //word length of current segment
 int AcumLength;        //word length of current path

} NodeData;
typedef NodeData* Pnodedata;

/*---------------------------------------------------------------------------
this class gets test sentences from file and create a
testitem object for each sentence to get translation
---------------------------------------------------------------------------*/
class TTest
{
private:
public:
```

```
    TStringList *TestLines;   //test sentences from file.
    TTest(String filename);   //filenem= name of test file
    ~TTest();


    void GetTestItems(TLexLst *Lexlst[],int MaxPhraseLength, int TotNumSol);

};

/*-------------------------TTestItem-------------------------------------
testitem class process test string and get translations
for this String
/-----------------------------------------------------------------------*/

class TTestItem
{
private:
    TStringList *Translations;//Array that saves all n-best translations
    int MaxPhraseLen;  // the max. phrase length in Phrase Table objects
    int SolutionsCnt;  //the found translations count
    int TotalNeededcSolutions; //maximum need translation count.
    int CompletedPaths;//number of completed paths
    int UnCompletedPaths;//number of incomplete paths
    double AvgProbability;//the current average word probability.

    //a suplementary function that searches for a delimeter in a string
    //and returns all Preceeding chars
    String GetDelimit(String* StrSource,String Delimit);

    //backtrack path to get complete translation
    //to save it in the translation table .
    Get_Total_Trans(TTreeNode *Node);

    //Add term in the translation table ordered by probability.
    Add_Term(String Translation,float Probability);

    Get_Word_List(TStringList *Word_List,String SourceString);
    String Get_Segment(TStringList *Word_List,int WordCount)

public:


    TTestItem(int PTotalitno, int PMaxPhraseLen);

    // Search algorithm generates translation tree.
    int GetSegmentTrans(TLexLst *Lexlst[],String TestRemainigString,
                        TTreeNode *ParentTransNode);
    ~TTestItem();
};
```

```
//---------------------------------------------------------------------------

TTreeView *TransSegTree;

#endif
```

Main Classes Implementation

```
//---------------------------------------------------------------------------


#pragma hdrstop

#include "test.h"
#include "Unit4.h"
#include "Math.h"

//---------------------------------------------------------------------------
// Load test sentences from file
TTest::TTest(String filename)
{
      TransSegTree= new TTreeView;
      TestLines=new TStringList;
      TestLines->LoadFromFile(filename);

}

//---------------------------------------------------------------------------
TTest::~TTest()
{
      delete TestLines;
      delete TransSegTree;
}

//---------------------------------------------------------------------------
// Function loops on testlines and generate testitem object
// for each to get translations
//




void TTest::GetTestItems(
            TLexLst *Lexlst[],   //array of Phrase table objects
            int MaxPhraseLength, //maximum phrase length that could be
                        //translated from Phrase table objects.
             int TotNumSol   //number of needed translation option per sent.
```

```
                )
{
    String CurStr;
    for (int i=0;i<TestLines->Count;i++)
    {
        //Create New Test sentence Object
      TTestItem *TestItem=new TTestItem(TotNumSol, MaxPhraseLength);

        // Create New node to be the root node for this test sentence
      TTreeNode *ChNode=
          TransSegTree->Items->AddChild(TransSegTree->Items->Item[0],
                                TestLines->Strings[i]);

        //Start Translation search
      TestItem->GetSegmentTrans(Lexlst,TestLines->Strings[i],ChNode);
    }
}

//---------------------------------------------------------------------------
TTestItem::TTestItem(int PTotalitno, int PMaxPhraseLen)
{

    Translations=new TStringList;
    AvgProbability=0;
    CompletedPaths=0;
    UnCompletedPaths=0;
    SolutionsCnt=0;
    TotalNeededcSolutions= PTotalitno;
    MaxPhraseLen = PMaxPhraseLen;
}
//---------------------------------------------------------------------------
TTestItem::~TTestItem()
{
    delete Translations;

}


//---------------------------------------------------------------------------
// This is the implementation of the decoder search algorithm
//
int TTestItem::GetSegmentTrans(
          TLexLst *Lexlst[], //pointer to array of Phrase tables Obj.
          String TestRemainigString, //Remaining string
          TTreeNode *ParentTransNode) //Parent node
{

  TStringList *TestRemainingWords=new TStringList;// array of remaining words
  String TransLation;
```

```
float Probability;
String CurrSegment;
String NewRemainingStr;


   // add remaining words to remaining array.

   Get_Word_List(TestRemainingWords,TestRemainigString);

   // Loop for all possible segments of length 1 to MaxPhraseLen from the
   //begining of Remaining part of TestSentence
   for (int j=0;j<MaxPhraseLen ;j++)
   {
      // Check if Len of Remaining words >= Current PhraseLen
       if (TestRemainingWords->Count > MaxPhraseLen-j)
        {
          TransLation="";

          CurrSegment=Get_Segment(TestRemainingWords,MaxPhraseLen-j);

         // searches for the segment in the Phrase table and
         // return translation and probability
          Probability=Lexlst[j]->GetTrans(CurrSegment,&TransLation);

         // a new node to save current segment translation data
          TTreeNode *ChNode=
                  TransSegTree->Items->AddChild(ParentTransNode,
                                        CurrSegment);
         // saving data in the node
           NodeData *Ndata= new NodeData;
           Ndata->Translation=TransLation;
           Ndata->Probability=Probability;
           Ndata->Length=MaxPhraseLen-j;

         // If Parent is Not Root Node
           if (ParentTransNode->Data!=0)
            {
              Ndata->AcumLength=Ndata->Length +
                    Pnodedata(ParentTransNode->Data)->AcumLength;

              Ndata->AcumProbability=Probability *
                (Pnodedata(ParentTransNode->Data)->AcumProbability);
            }
           else
           {
             Ndata->AcumProbability=Probability;
             Ndata->AcumLength=Ndata->Length;
           }
           ChNode->Data=Ndata;
```

```
                // get remaining string to be passed to the same function to
                // go one level down in the tree
                   NewRemainingStr=TestRemainigString;
                   GetDelimit(&NewRemainingStr,CurrSegment);

                // check if the list of best trans. is not yet full OR
                // the current word probability is greater than history avg.
                   if ((SolutionsCnt<=TotalNeededcSolutions)
                     ||(pow(Ndata->AcumProbability, 1.0/Ndata->AcumLength)
                           >=AvgProbability))
                    {
                       // If not last node in current path
                     if (Trim(NewRemainingStr)!="")
                       {
                         GetSegmentTrans(Lexlst,NewRemainingStr,ChNode);
                       }
                     else // last node
                       {
                         //get total translation & Add Trans to N-Best
                         //list
                        Get_Total_Trans(ChNode);
                        CompletedPaths++;
                       }
                    }
                    else // Prune this path
                      UnCompletedPaths++;

            }//if (TestRemainingWords->Count > MaxPhraseLen-j)
      }//for (int j=0;j<MaxPhraseLen ;j++)

      delete TestRemainingWords;
}

//---------------------------------------------------------------------------
//
String TTestItem::GetDelimit(String* StrSource,String Delimit)
{
   String result=MidStr(*StrSource,0, StrSource->AnsiPos(Delimit)-1);
   *StrSource=MidStr(*StrSource,StrSource->AnsiPos(Delimit)+ Delimit.Length(),
                StrSource->Length());
   return (result);
}

//---------------------------------------------------------------------------

TTestItem::Get_Total_Trans(TTreeNode *Node)
{
   TTreeNode *PNode=Node;
```

```
  String TotalTranslation=Pnodedata(PNode->Data)->Translation;
  // backtrack segment translations for this path to get full translation
  while (PNode->Parent->Data!=0)
  {
   PNode=PNode->Parent;
   TotalTranslation=Pnodedata(PNode->Data)->Translation+" "+TotalTranslation;
  }
  TotalTranslation=TotalTranslation
                + "\t" +
                Pnodedata(Node->Data)->AcumProbability
                + "\t" +
                FloatToStr(pow(Pnodedata(Node->Data)->AcumProbability,
                        1.0/Pnodedata(Node->Data)->AcumLength));


  // Add translation in orderd list of n-best translation
  Add_Term(TotalTranslation,Pnodedata(Node->Data)->AcumProbability);
  SolutionsCnt++;
}
//---------------------------------------------------------------------------
TTestItem::Add_Term(String Translation,float Probability)
{
    String CurrProb;
    String CurrString;
    int GreaterFound=0;
    // add new entry in translation list with probability order
    if  (Translations->Count==0)//first entry
    {
        Translations->Add(Translation);
    }
    else
    {
        // loop to get the right posistion (in probability order)
        // to add the new translation
        for (int i=0;i<Translations->Count ;i++)
        {
            CurrString=Translations->Strings[i] ;
            GetDelimit(&CurrString,"\t");
            CurrProb=GetDelimit(&CurrString,"\t");
            if (Probability> StrToFloat(CurrProb))
            {
                GreaterFound =1;
                Translations->Insert(i,Translation);
                i=Translations->Count; //break;
            }
        }

        // if it is the least probability so i add it as the last one
        if (GreaterFound ==0)
```

```
            {
                Translations->Add(Translation);
            }
        }
        // check if the count exceeded total count needed
        // so delete the last one (least probability)
        if (Translations->Count>TotalNeededcSolutions)
        {
            Translations->Delete(TotalNeededcSolutions);
        }

        //Get New Avg word probability
        CurrString=Translations->Strings[Translations->Count-1];
        GetDelimit(&CurrString,"\t");
        GetDelimit(&CurrString,"\t");
        AvgProbability=StrToFloat(CurrString); // save new probability
}

//---------------------------------------------------------------------------

TTestItem::Get_Word_List(TStringList *Word_List,String SourceString);
{
    String Temp=SourceString+" ";
    while (Temp !="")
        Word_List->Add(GetDelimit(&Temp," "));

}
//---------------------------------------------------------------------------
String TTestItem::Get_Segment(TStringList *Word_List,int WordCount);
{

    String Segment=Word_List->Strings[0];
    for (int z=1; z<WordCount; z++)
    {
        Segment=Segment+" "+TestRemainingWords->Strings[z+1];
    }
    return (Segment);
}

//---------------------------------------------------------------------------
#pragma package(smart_init)
```

Appendix D

Sample Translations

Translation Direction : English to Arabic
Corpus : Mobile
Model Used: IBM model 4

Human Translation	Model 4 Translation	Edit Distance
$ أثناء استخدام سماعة الأذن احمل الراديو كأي هاتف آخر مع مراعاة أن الهوائي متجه إلى الأعلى خلف الكتف .	$ عند الأذن' ستخدم ، الاستمرار الراديو كما التي فعلى أي telephone مع الهوائي متجه يصل مع بمرور بك الكتف .	43.40
$ إن هذا الراديو ، كأي هاتف لاسلكي ، يعمل باستخدام الإشارات الاسلكية والشبكات الاسلكية والشبكات الأرضية بالإضافة إلى وظائف يحدها المستخدم .	$ هذا الراديو ، تفعل أي الاسلكية الهاتف ، تبع استخدام الراديو إشارات ، الاسلكية مع الأرضية الشبكات كما أقل كما المستخدم - المبرمج وظائف .	41.01
$ ولا يمكن ضمان الاتصال في كل الأحوال .	$ لأن من هذا ، وgprs في جميع ظل يمكنك لا تكون مضمونة .	27.78
$ لذا لا تعتمد كليًا على الهاتف الاسلكي في الاتصالات الضرورية (حالات الطوارئ الطبية مثلا) .	$ لذا التي ينبغي أبدًا الضرورية الضرورية تحده أي الاسلكية الهاتف لمدة مطلبًا اتصالات (e . g . المعدات مثلا) .	41.44
$ قد لا تكون مكالمات الطوارئ مكنة على كافة شبكات خدمة الهواتف الاسلكية أو عندما تكون بعض خدمات الشبكة و / أو خصائص الراديو قيد الاستخدام .	$ الطوارئ مكالمات قد لا تكون قدر فوق جميع الاسلكية الهاتف الشبكات أو عند معينة الشبكة خدمات مع / أو الراديو مزايا يتم في استخدام .	43.48
$ تأكد من ذلك من المزود المحلي لخدمة الخلوية المحلية .	$ فحص مع المحلية الخدمة مزودو .	38.89
$ يمكن إجراء مكالمات الطوارئ فقط في وضع الشبكة .	$ الطوارئ مكالمات يمكنك فقط تكون إجراؤها في الشبكة وضع .	39.29
$ إذا كان الراديو في الوضع المباشر ، قم أولا بتنشيط وضع الشبكة :	$ إذا الراديو' في المباشر وضع ، أولا نش الشبكة وضع :	56.92
$ لإجراء مكالمة طوارئ :	$ إلى بإجراء تحت الطوارئ مكالمة :	45.45
$ افتح الراديو إذا لم يكن مفتوحًا .	$ إذا الراديو' لا فوق ، قم ذلك فوق .	43.24
$ تأكد من وجود إشارة كافية .	$ فحص لمدة يحتويها إشارة قوة .	43.33
$ اضغط على (graphic) عدة مرات (مثلا لإنهاء مكالمة ، الخروج من الائحة وإلخ) حتى إخلاء الشاشة وتجهيز الراديو لإجراء المكالمات .	$ اضغط (graphic) كما العديد أوقات كما الحاجة (e . g . إلى لخروج مكالمة ، إلى لخروج القائمة ، إلخ .) إلى إخلاء شاشة مع جاهز الراديو لمدة مكالمات .	53.02
$ أدخل رقم الطوارئ لمنطقتك الحالية (مثل ١٢ أو أي رقم طوارئ رسمي آخر) .	$ مفتاح في الطوارئ رقم لمدة بك أصل (e . g . location ١٢ أو الأخرى رسمي الطوارئ رقم) .	43.68
$ تختلف أرقام الطوارئ من مكان إلى آخر .	$ الطوارئ أرقام تختلف بواسطة . location	25.64
$ اضغط على مفتاح (graphic) .	$ اضغط (graphic) مفتاح	50.00
$ إذا كانت بعض الخصائص قيد الاستخدام فقد تحتاج إلى غلقها قبل أن تمكن من إجراء نداء طارئ .	$ إذا معينة مزايا يتم في استخدام ، التي قد أولا يلزم إلى دورك عيد مزايا من قبل التي يمكنك بإجراء تحت الطوارئ مكالمة .	38.14
$ راجع هذا الدليل مع وكيل الخدمة المحلي لخدمات الخلوية .	$ استشر هذا الدليل مع بك المحلية الخلوية الخدمة مزود .	55.36
$ عند عمل نداء ، احرص على إعطاء كافة المعلومات المطلوبة بدقة .	$ عند إجراء تحت الطوارئ مكالمة ، تذكر إلى أخبرهم جميع لزم المعلومات كما بدقة كما قدر .	38.37
$ تذكر أن الهاتف هو ربما الوسيلة الوحيدة لاتصال من موقع الحادث - فلا تنه النداء قبل أن يطلب منك ذلك .	$ تذكر أن بك الراديو قد تكون فقط كتابي من comunication الحادث من تحت الحادث - لا لا قص من مكالمة حتى مفصلة إذن إلى لا لذا .	37.40
$ انقر فوق اسم الصورة التي تريد حذفها ، ثم انقر فوق رمز # (حذف) (. delete)	$ انقر فوق اسم من الإلكتروني التي ترغب إلى حذف ، مع انقر فوق حذف الرمز .	48.72
$ يقوم nokia pc sync بعمل تكرارات عند مزامنة جهات اتصال بعد استعادتها بواسطة nokia	$ الشخصية nokia pc sync بعمل تكرارات عند i am التزامن جهات بعد لديه استعادتها المواقع مع . nokia content copier	71.17

		. content copier
23.53	$ slideshow $خصائص	$ خصائص الشرائح
41.18	$ جديدة الحافظة .	$ حافظة جديدة .
54.55	$ لخروج التقديمي	$ إنهاء العرض التقديمي
40.38	$ مع الخلفي من الهاتف مواجهتك التي ، push الخلفي غطاء التحرير الزر (١) مع إزالة غطاء من الهاتف (٢) .	$ وظهر الهاتف يتجه إليك ، اضغط على زر تحرير الغطاء الخلفي (١) وأزح الغطاء الخلفي بعيدًا (٢) .
46.07	$ انتقل إلى المطلوبة اسم أو رقم ، مع اضغط " " " qtn_softk_view_number " على " عرض " " " .	$ انتقل إلى الاسم أو الرقم المطلوب ، واضغط على " عرض " .
40.35	$ الوظيفة من الهاتف مفاتيح قد تختلف في مختلفة wap خدمات .	$ قد تختلف وظائف مفاتيح الهاتف باختلاف خدمات wap .
63.27	$ إرشادات لمدة مقابل لمدة بك المشتريات مع المحفظة	$ إرشادات سداد مقابل المشتريات بواسطة المحفظة
38.61	$ الوميض يستمر لمدة تقريبًا ١٠ دقائق أو حتى الرأس' توصيل إلى متوافق الهاتف .	$ قد يستمر الوميض لمدة ١٠ دقائق تقريبًا ، أو حتى يتم توصيل سمّ اعة الرأس بهاتف متوافق ، أيهما أقرب .
100.00	$ الهاتف :	$ الهاتف :
35.00	$ التي يجب suply المفعول حساب التفاصيل .	$ يجب عليك توفير تفاصيل الحساب الصحيح .
37.93	$ بالعمل المحمول	$ الهاتف المحمول الخاص بالعمل
60.53	$ إزالة الم المسار (s) مع / أو قائمة (s) من الجهاز .	$ إزالة المسار (المسارات) المحد و / أو قائمة (قوائم) التشغيل من الهاتف .
21.28	$ الأسلاك رباعية واجهة ((g 4 wif	$ generaltagpurpose fourtagwire interface) الواجهة رباعية الأسلاك ذات الغرض العام wif 4 g : ( )
47.06	central procesing $وحدة	central procesing unit ( ) $وحدة المعالجة المركزية)
100.00	$ sws	$ sws
58.82	$ اضغط التحرير الزر أسفل من الراديو لخلف إلى فتح البطارية غطاء .	$ اضغط على زر التحرير الموجود أسفل الراديو لخلف لفتح غطاء البطارية .
59.66	$ إذا التي لديك لمزيد أكثر واحد رقم المحفوظة تحت اسم ، انتقل إلى المطلوبة رقم مع اضغط " " " موافق " على " موافق " " " .	$ إذا توفر لديك أكثر من رقم محفوظ تحت الاسم ، فانتقل إلى الرقم المطلوب واضغط على " موافق " .

Translation Direction : English to Arabic
Corpus : Mobile
Model Used: Our Phrase model

Human Translator	Our Translation	Edit Distance
$ أثناء استخدام سماعة الأذن احمل الراديو كأي هاتف آخر مع مراعاة أن الهوائي متجه إلى الأعلى خلف الكتف .	$ عند سماعة الأذن ، فسيتم ، احمل الراديو كأي هاتف الهوائي الأعلى لأعلى خلف الكتف .	55.88
$ إن هذا الراديو ، كأي هاتف لاسلكي ، يعمل باستخدام الإشارات الاسلكية والشبكات الاسلكية والشبكات الأرضية بالإضافة إلى وظائف يحدها المستخدم .	$ هذا الراديو ، كأي هاتف لاسلكي ، يعمل باستخدام الإشارات الاسلكية والشبكات الاسلكية والشبكات الأرضية بالإضافة إلى وظائف يحدها المستخدم .	97.12
$ ولا يمكن ضمان الاتصال في كل الأحوال .	$ ولا الاتصال في كل الأحوال يمكن ضمان .	48.72
$ لذا لا تعتمد كليًا على الهاتف الاسلكي في الاتصالات الضرورية (حالات الطوارئ الطبية مثلا) .	$ لذا لا تعتمد كليًا على الهاتف الاسلكي الاتصالات الضرورية (. حالات الطوارئ الطبية مثلا) .	94.62
$ قد لا تكون مكالمات الطوارئ مكنة على كافة شبكات خدمة الهواتف الاسلكية أو عندما تكون بعض خدمات الشبكة و / أو الراديو الخصائص قيد الاستخدام .	$ قد لا تكون مكالمات الطوارئ مكنة على كافة شبكات خدمة الهواتف الاسلكية أو عندما تكون بعض خدمات الشبكة و / أو الراديو الخصائص قيد الاستخدام .	92.14
$ تأكد من ذلك من المزود المحلي لخدمة الخلوية المحلية .	$ تأكد من ذلك المزود المحلي لخدمات الخلوية المحلية .	90.74
$ يمكن إجراء مكالمات الطوارئ فقط في وضع الشبكة .	$ الطوارئ يمكن إجراء في وضع الشبكة .	47.92
$ إذا كان الراديو في الوضع المباشر ، قم أولاً بتنشيط وضع الشبكة :	$ إذا كان الراديو في الوضع المباشر ، قم أولا قم بتنشيط وضع الشبكة :	95.59
$ لإجراء مكالمة طوارئ :	$ إلى لإجراء مكالمة طوارئ :	85.19
$ افتح الراديو إذا لم يكن مفتوحًا .	$ إذا كان الراديو لم يكن مفتوحا .	68.57
$ تأكد من وجود إشارة كافية .	$ تأكد من وجود إشارة كافية .	100.00
$ اضغط على (graphic) عدة مرات (مثلا لإنهاء مكالمة ، الخروج من الائحة وإلخ) حتى إخلاء الشاشة وتجهيز الراديو لإجراء المكالمات .	$ اضغط على # عدة مرات (على سبيل المثال لإنهاء مكالمة ، الخروج الائحة والخ) حتى إخلاء الشاشة وحت ويكون الهاتف مستعدًا لإجراء المكالمات واستلامها .	65.99
$ أدخل رقم الطوارئ لمنطقتك الحالية (مثل ١٢ أو أي رقم طوارئ رسمي آخر) .	$ أدخل رقم الطوارئ لمنطقتك الحالية (١٢ أو أي رقم رسمي آخر لطوارئ) .	76.39
$ تختلف أرقام الطوارئ من مكان إلى آخر .	$ تختلف أرقام الطوارئ من مكان آخر .	89.74
$ اضغط على مفتاح (. (graphic	$ اضغط على المفتاح ((graphic	86.67
$ إذا كانت بعض الخصائص قيد الاستخدام فقد تحتاج إلى غلقها قبل أن تمكن من إجراء نداء طارئ .	$ إذا كانت بعض الخصائص قيد ، فقد تحتاج هذه قبل أن إجراء نداء طارئ .	71.91
$ راجع هذا الدليل مع وكيل الخدمة المحلي لخدمات الخلوية .	$ راجع هذا الدليل مع وكيل الخدمة المحلي لخدمات الخلوية .	100.00
$ عند عمل نداء ، احرص على إعطاء كافة المعلومات المطلوبة بدقة .	$ عند عمل نداء ، كافة المعلومات . accurately	54.84
$ تذكر أن الهاتف هو ربما الوسيلة الوحيدة لاتصال من موقع الحادث - فلا تنه النداء قبل أن يطلب منك ذلك .	$. تذكر الراديو أن هو ربما الوسيلة الوحيدة لاتصال موقع الحادث – فلا تنه النداء قبل أن يطلب قص الاتصال منك ذلك .	75.89
$ انقر فوق اسم الصورة التي تريد حذفها ، ثم انقر فوق رمز # (حذف) (. (delete	$ انقر فوق اسم الصورة التي تريد حذفها ، ثم انقر فوق رمز . delete	82.05
$ يقوم nokia pc sync بعمل تكرارات عند مزامنة جهات اتصال بعد استعادتها بواسطة . nokia content copier	$ يقوم nokia pc sync بعمل تكرارات عند إجراء التزامن جهات اتصال بعد استعادتها بواسطة . nokia content copier	90.57
$ خصائص الشرائح	slideshow $خصائص	23.53
$ حافظة جديدة .	$ حافظة جديدة .	100.00
$ إنهاء العرض التقديمي	$ إنهاء العرض التقديمي	100.00

52.58	$ مع الهاتف اتجاه التي اضغط الغطاء الخلفي زر التحرير (١) واسحب الغطاء الهاتف (٢) .	$ وظهر الهاتف يتجه إليك ، اضغط على زر تحرير الغطاء الخلفي (١) وأزح الغطاء الخلفي بعيدًا (٢) .
45.95	$ انتقل إلى الاسم المطلوب أو ورقم اضغط على " qtn_softk_view_number " " " .	$ انتقل إلى الاسم أو الرقم المطلوب ، واضغط على " عرض " .
64.00	$ وظائف مفاتيح الهاتف قد تختلف باختلاف خدمات . wap	$ قد تختلف وظائف مفاتيح الهاتف باختلاف خدمات . wap
65.22	$ إرشادات دفع تكاليف مشترياتك باستخدام المحفظة	$ إرشادات سداد مقابل المشتريات بواسطة المحفظة
67.33	$ يشير المؤشر الوامض يستمر لمدة ١٠ دقائق تقريبًا ، أو حتى يتم توصيل سمّ اعة الرأس إلى هاتف متوافق .	$ قد يستمر الوميض لمدة ١٠ دقائق تقريبًا ، أو حتى يتم توصيل سمّ اعة الرأس بهاتف متوافق ، أيهما أقرب .
100.00	$ الهاتف :	$ الهاتف :
48.72	$ يجب مصدر صالح ال & حساب التفاصيل .	$ يجب عليك توفير تفاصيل الحساب الصحيح .
100.00	$ الهاتف المحمول الخاص بالعمل	$ الهاتف المحمول الخاص بالعمل
100.00	$ إزالة المسار (المسارات) المحد و / أو قائمة (قوائم) التشغيل من الهاتف .	$ إزالة المسار (المسارات) المحد و / أو قائمة (قوائم) التشغيل من الهاتف .
62.77	generaltagpurpose $واجهة رباعية الأسلاك ذات غرض عام (g 4 wif)	$ generaltagpurpose fourtagwire interface ( )الواجهة رباعية الأسلاك ذات الغرض العام g 4 wif : ( )
96.08	central procesing unit $وحدة المعالجة المركزية ( )	central procesing unit $وحدة المعالجة المركزية ( )
100.00	$ sws	$ sws
85.29	$ اضغط على زر التحرير عند أسفل الراديو لخلف إلى افتح غطاء البطارية .	$ اضغط على زر التحرير الموجود أسفل الراديو لخلف لفتح غطاء البطارية .
77.17	$ إذا أكثر من رقم محفوظ تحت الاسم وانتقل إلى الرقم واضغط على " موافق " .	$ إذا توفر لديك أكثر من رقم محفوظ تحت الاسم ، فانتقل إلى الرقم المطلوب واضغط على " موافق " .