A Probabilistic Model of Machine Translation

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Abstract

A probabilistic model for computer-based generation of a machine translation system on the basis of English-Russian parallel text corpora is suggested. The model is trained using parallel text corpora with pre-aligned source and target sentences. The training of the model results in a bilingual dictionary of words and "word blocks" with relevant translation probability.

1 Introduction.

The corpus-based statistical MT gains more popularity nowadays due to vastly increased capacity of modern computers. The works of P. Brown and collaborators [1, 2], may be regarded as a typical recent example.

This paper suggests another approach to statistical MT different from that of Brown et al. The suggested model is trained on pre-aligned bilingual text corpora and the following approach to 'tailor making’ a computer dictionary and an MT system is taken. The translation of a source word combination by a target one is determined by the correlation with the neighboring word combinations both in the source and the target texts rather than only by the translation probabilities of the combinations themselves.

The word order of the source and target sentences seldom coincide, however, the raw translation with the incorrect order of words may often be understood by a specialist. The translation quality will radically improve if instead of individual words one takes internally agreed word combinations with fixed order (blocks).

In this model statistically stable source blocks are related to the most probable target ones using specially introduced function, called "adhesion function" since it is believed that this function indirectly reflects the grammatical and semantic "adhesion" of the words in a text. We believe that blocks with negative correlation having been excluded the remaining internally agreed blocks in a way will become a substitute of the proper word order in the target sentence.

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2 Probability Assessment and Model Training.

The training corpus is presumed to be pre-aligned, i.e. divided into the matching pairs of the source and target sentences\(^1\). Each of the sentences comprising a pair is broken into the word sequences (blocks) in such a way that the order of words a sequence had in the sentence is preserved.

The first block comprises the first words of matching sentences, then one word is added each time until the block reaches the extreme length\(^2\). Then the procedure is repeated starting from the second word and so on. All the blocks obtained in the above manner are stored in temporary data file with the blocks that appear several times being regarded at this stage as different (viz. Fig. 1).

![Fig.1. Diagram illustrating the breaking of the sentence into blocks.](image)

We suggest two alternative procedures for the sorting-out of the preliminary data file to obtain the translation dictionary.

Let in a sentence of a length \(L\) number of \(b\) words blocks is \(L - b + 1\). Total number of blocks with the length that does not exceed \(l\) in this sentence is

\[
N_l = \sum_{b=1}^{l} (L - b + 1) = \frac{l(2L - l + 1)}{2} \leq N_L = \frac{L(L + 1)}{2} \tag{1}
\]

Number of block pairs

\[
N_l^{(S)} \times N_l^{(T)} = \frac{l^2 (2L^{(S)} - l + 1) (2L^{(T)} - l + 1)}{4} \tag{2}
\]

where \(L^{(S)}\) and \(L^{(T)}\) are lengths of source and target sentences correspondingly.

Even in a texts where lengths of source and target sentences are large enough (say \(L^{(S)} = L^{(T)} = 20\) )

We see that whole volume of block pairs less then 14 times larger then the number of block pairs with the length that does not exceed \(l = 3\).

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\(^1\)In the training corpus as well as in the translated texts the ends of sentences are presumed to be marked with common punctuation marks.

\(^2\)In our case the minimal length limit of a block is three words.
\[ N_l^{(S)} = N_l^{(T)} \]
\[ N_3^{(S)} = N_3^{(T)} \]
\[ N_20^{(S)} \times N_20^{(T)} \]
\[ N_3^{(S)} \times N_3^{(T)} \]
\[ N_20^{(S)} \times N_20^{(T)} \]

**Table 1**

| \( N_l^{(S)} \) | \( N_l^{(T)} \) | \( N_3^{(S)} \) | \( N_3^{(T)} \) | \( N_20^{(S)} \times N_20^{(T)} \) | \( N_3^{(S)} \times N_3^{(T)} \) | \( N_20^{(S)} \times N_20^{(T)} \) |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 420             | 114             | 176400          | 12996           | 13573           |                  |                  |

**2.0.1 a) ”All-In” Relations Alternative.**

1. In this case the sentence pairs are broken into arbitrary number \( v \) and \( \bar{v} \) of the blocks.

2. If the number of different blocks, \( v \), obtained after all possible divisions of a sentence is greater than the number of blocks, \( \bar{v} \), obtained in its counterpart, the latter is added with blank blocks until the number of blocks in both target and source sentences becomes equal \( w = \max(v; \bar{v}) \).

3. Let us relate each block of the source (English) sentence with its all target (Russian) counterparts.

4. The resulting \( w \) pairs \( \{S_j, T_k\} ; j = 1, 2, ..., w \) are stored in the temporary data file.

**2.0.2 b) Symmetrical Relations Alternative.**

1. In this case the sentence pairs are broken into the equal number \( w \) of the blocks having no blank counterparts. Moreover, only the blocks with the same value of \( j \) are stored in the preliminary data file.

2. Then for each division we shall have \( w \) pairs \( \{S_j, T_j\} ; j = 1, 2, ..., w \).

3. The resulting \( w \) pairs \( \{S_j, T_k\} ; j, k = 1, 2, ..., w \) are stored in the temporary data file.

The symmetrical alternative will require a bigger training corpus, however, it will allow to use the same block comparison procedure in training and in translation.

In both alternatives the procedure of sentence division will be terminated when the computer storage capacity is exhausted.

Let then \( n = \sum w^2 \) be the total number of the matching block pairs of the alternative ”a” \( n = \sum w^2 \) be that of the alternative ”b”. Then the total number of the source blocks \( S = (s_1, s_2, ...) \), that of the target blocks \( T = (t_1, t_2, ...) \) and the total of the pairs \( \{S, T\} \) will be given by \( n^S \), \( n^T \), \( n^{S \cap T} \), whereas the relevant probabilities \( P^S \), \( P^T \) and \( P^{S \cap T} \) will be found from:

\[
P^T = \frac{n^T}{n}; \quad P^S = \frac{n^S}{n}; \quad P^{T \cap S} = \frac{n^{T \cap S}}{n} \tag{3}
\]

Then the conventional probability \( P(T|S) = P^{T \cap S}/P^S \) of the word \( T \) as a translation of the word \( S \) and the probability \( P(S|T) = P^{T \cap S}/P^T \) of the word
as a translation of the word are related by Bayes formula

\[ P(T|S)P^S = P^{TS} = P(S|T)P^T \]

(4)

As it is well known, the correlation between the events and will be

\[ C^{TS} = P^{TS} - P^S P^T \]

(5)

When events \( S \) and \( T \) are independent, i.e. co-occur at random, \( P^{TS} = P^S P^T \), the correlation function \( C^{TS} \) becomes zero. Then it may be suggested that the negative correlation \( C^{TS} < 0 \) will be the case, when the source and target language words are so eager to avoid each other, that their correlated co-occurrence is less probable than the random one. We regard such co-occurrences as prohibited by the rules of the languages involved.

The correlation analysis starts from the minimal, one-word blocks \( S = (s_1), T = (t_1) \). The longer two-word \( S = (s_1, s_2), T = (t_1, t_2) \) and three-word \( T = (t_1, t_2, t_3), S = (s_1, s_2, s_3) \) ones are analysed if

\[ \rho^{S_j \cap S_{j+1}} = C^{S_j \cap S_{j+1}} / P^S j P^{S_{j+1}}; \quad \rho^{T_j \cap S_{j+1}} = C^{TS} / P^S j P^T \]

(9)

to satisfy the condition

\[ \rho^{S_j \cap S_{j+1}} > c^S_+; \quad \rho^{S_j \cap S_{j+1}} < - c^-_S \]

(10)

\[ \rho^{T_j \cap T_{j+1}} > c^T_+; \quad \rho^{T_j \cap T_{j+1}} < - c^-_T \]

(11)

\[ \rho^{T_j \cap S_k} > c^{TS}_+; \quad \rho^{T_j \cap S_k} < - c^{-TS} \]

(12)

All pairs \( S_j \cup S_{j+1}, \text{consisting of sub-blocks } S_j \text{ and } S_{j+1} \) will be included in \( S \)-dictionary, if sub-blocks \( S_j \) and \( S_{j+1} \) satisfy the condition \( \text{(10)} \). Similarly
if sub-blocks $T_j$ and $T_{j+1}$ satisfy the condition they are included in a $T$-dictionary. And, finally, if the condition is satisfied, we include $(T_j, S_k)$ pairs into $T S$-dictionary. The values of positive constants $c^S_T$, $c^T_S$ and $c^{TS}_T$ naturally depend on the computer storage capacity. In this way we shall be able to calculate both $P(S|T)$ and $P(T|S)$ which will allow to reverse the direction of the translation.

All the elements of a word paradigm enter the dictionaries as separate entries. Both the selection of a correct (and strongly prohibited) form for translation and agreement between the forms are achievable, on the one hand, because the forms within a block are already agreed and, on the other, because reasonable agreement of paradigm forms in matching blocks is obtained in the course of maximisation, as described below.

The training may be simplified if we have a dictionary of cognates. In this case the preliminary data file will not include the pairs in which one block comprises a cognate whereas its counterpart does not. When the dictionary is generated (i.e. available amount of training corpora is exhausted), we pass over to the translation using a new text.

3 Translation Model Optimisation

The translation of a new sentence starts from dividing it into blocks. This is being done in such a way that none of the blocks is wholly contained in any other. To satisfy this condition any next block will begin with, at least, one word after the first word of the previous block and will end with, at least, one word after the last word of the preceding block. Each of the source blocks will be related to the target ones.

The division starts from the blocks of the maximum length available in the dictionary, and the block length is gradually decreased to the word-to-word pairs. To select the optimal translations we shall use the following maximisation procedure.

For the words in a source (or target) text we suggest the characteristic of ‘adhesion’. We shall call “adhered” both the words which enter one and the same block and those entering the overlapping blocks. Thus, in Fig. 1 the words $abc$, $bcd$, $cdef$ and $gh$ adhere into blocks and since the words $b$, $c$, $d$ enter several blocks simultaneously they are also considered adhered. Words $ag$, $ah$, $bg$, $bh$ and so forth are not adhered. Fig 1. shows the source sentence only. It is understood that for simplicity the target sentence will have the same block pattern. Naturally, in both texts the blocks with multiple overlapping will be those having greater adhesion. At the same time, the longer is the block the smaller is its occurrence probability in the dictionary after training. For equal competition opportunities for longer and shorter blocks the following procedure is suggested. To illustrate this let us consider the blocks of maximum two words

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4 The cognates are the words of similar graphic image in different languages, e.g. syntax and sintaksis.

5 Identification and use of cognates may be found, e.g., in [3] and [4].
Fig. 2. A Diagram of a 3-Word Sentence Translated by Two Overlapping Blocks.

and assume that a three-word sentence is translated by the two linked blocks (Fig. 2).

Of course, all the words in Fig. 2 are adhered and the source sentence cannot be translated by one target sentence only because of our two-word block constraints. We suggest the following model-type relation to compute the true probability:

\[ P(t_1, t_2, t_3) \approx P(t_1, t_2) P(t_2, t_3) f(P(t_2)) \]

i.e. we suggest that the relation of the true probability to the probabilities of the individual blocks, \( P(t_1, t_2) \) and \( P(t_2, t_3) \), depends only on the probability of the overlapping words \( P(t_2) \).

\[ f(P(t_2)) \]

Generally speaking, finding the overlapping probability function \( f(P(t_2)) \) requires a special phenomenological study, but for our model we limit ourselves with the following simple considerations. It is easy to see that if all the words are not adhered with the others, then

\[ P(t_1, t_2, t_3) \approx P(t_1) P(t_2) P(t_3) \]

and hence having substituted (14) into (13) we obtain for this very special case:

\[ f(P(t_2)) \approx \frac{1}{P(t_2)} \]

We hope that this approximation will give satisfactory results for the general case, that is why we assign the factor \( 1/P \) each time the words in blocks overlap.

The function \( f(P(t_2)) \) is introduced to accord the blocks and its form is presumed to be universal for the given language. We shall call it global adhesion factor (GAF). A more effective way to account for the overlapping of the blocks is to introduce local adhesion factor (LAF) for each word rather than GAF:

\[ f_{t_2} = \frac{P(t_1, t_2, t_3)}{P(t_1, t_2) P(t_2, t_3)} \]

LAF \( f_{t_2} \) for each \( t_2 \)-word is at first computed for all \( P(t_1, t_2, t_3), P(t_1, t_2) \) and \( P(t_2, t_3) \) available and then averaged over \( t_1 \) and \( t_3 \). In this case \( f_{t_2} \) really becomes an inherent characteristic of an \( \tilde{t}_2 \)-word. It easy to see that in \( P(S|T) = P(S|T) / P(T) \) the overlapping of \( \tilde{t}_1 \)-words is present both in \( P(S|T) \) and \( P(T) \), hence,

\footnote{For the sake of simplicity we show the adhesion function only for the target blocks, it is understood, however, that similar function is calculated in the same way for the source blocks as well.}
LAF values for \( t \)-words are cancelled, then during translation stage we take into account only LAF for \( s \)-words. Then for a sentence we have:

\[
F^S_L = \prod_j F^S_j \cap S_{j+1} = \prod_j \left[ \prod_{\tilde{\mu} \in S_j \cap S_{j+1}} f_{\tilde{\mu}} \right]
\]

(17)

where the product is computed over overlapping \( \tilde{s} \)-words.

An overlapping in the source sentences (e.g. \( s_2 \) in Fig. 2) may be related to that in the target sentence (e.g. \( t_2 \) in Fig. 2). During translation combining the target blocks we may get double occurrence of the overlapping word (e.g., when combining \( T = (t_1, t_2) \) and \( \tilde{T} = (t_2, t_3) \) we get double occurrence of \( t_2 \)), which are to be excluded from the translation product. One should also exclude the synonyms as well. Having excluded double occurrences we shall obtain a set of \( \mu = 1, 2, ... \) translation alternatives \( \{ T^\mu_k \cup T_{k+1}^\mu \} \) combining several neighboring blocks \( k \) and \( k+1 \), some of which may be grammatically incorrect.

We suggest the following correction procedure:

a) Each of \( \{ T^\mu_k \cup T_{k+1}^\mu \} \) alternatives is broken into all possible sub-blocks;

b) The optimal alternative is obtained by

\[
\max \left\{ \rho_{T^\mu_k \cap T_{k+1}^\mu} \right\}
\]

(18)

We believe that increasing the length of blocks we shall be able to select successfully the translation words corresponding to the source context. Moreover, one will hardly require fragments longer than four words, since correlation at such distances seems rather weak.

For the general case of translation probability maximisation we propose the following:

\[
\max \left\{ \prod_{j=1}^{N} \frac{P^{T^\mu_j S_j}}{P^{S_j} F^T_{j, j+1}} \right\}
\]

(19)

where \( P^{T^\mu_j S_j} = P(t_1, t_2, ..., t_n | s_1, s_2, ..., s_n) \) is the probability corresponding to block \( j \) in given translation alternative. The overlapping function \( F^T_{j, j+1} \) for \( n_{\mu} \)-fold overlapping of the words \( \tilde{t}_{\mu} \) in a neighbored blocks \( T_j \) and \( T_{j+1} \) may be computed as

\[
F^T_{L, j+1} = \left\{ \prod_{\tilde{\mu} \in T^\mu_j \cap T^\mu_{j+1}} f_{\tilde{\mu}} \right\}
\]

(see (17)). The maximisation procedure can be easily modified for the source language since the suggested model is evidently symmetrical.

\section{Conclusions}

Similar to [1] we train our model using parallel text corpora. However, our model is different in a number of aspects. We consider the suggested numerical correlation between source and target blocks (simultaneous interpreter principle) more critical for translation quality than selection of optimal word positions through the maximisation of the product of the relevant probabilities as in [1] [2]. For the model, suggested in this paper, there is room for perfection limited
only by computation capacity through increasing the block length. In the model of [1], [2], however, it is not clear, how without some new modelling ideas to make probability-based choice between, say, such two sentences as "He is alive, but she is dead" and "He is dead, but she is alive" both of which are correct grammatically, but controversial semantically.

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