

# Phrase Based Language Model for Statistical Machine Translation

Technical Report by

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# Abstract

Reordering is a challenge to machine translation (MT) systems. In MT, the widely used approach is to apply word based language model (LM) which considers the constituent units of a sentence as words. In speech recognition (SR), some phrase based LM have been proposed. However, those LMs are not necessarily suitable or optimal for reordering. We propose two phrase based LMs which considers the constituent units of a sentence as phrases. Experiments show that our phrase based LMs outperform the word based LM with the respect of perplexity and n-best list re-ranking.

Key words: machine translation, language model, phrase based

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# 1 Introduction

In the process of translation, reordering is a usual phenomenon. A LM is mainly used to reorder the sentences which were translated via the translation model.

Reordering generally occurs in phrase level. For example, when “小明前天打篮球” is translated to “Xiaoming played basketball the day before yesterday”, where “前天” is translated to “the day before yesterday” and “打篮球” is translated to “played basketball”, reordering occurs between “played basketball” and “the day before yesterday”.

However, the widely used word based LM is not necessarily optimal in this case. Also in the example above, in a bigram word based LM, the probability of “Xiaoming played basketball the day before yesterday” is

$$\begin{aligned} &P(\text{Xiaoming played basketball the day before yesterday}) \\ &= P(\text{Xiaoming} \mid \text{/start}) * P(\text{played} \mid \text{Xiaoming}) \\ & * P(\text{basketball} \mid \text{played}) * P(\text{the} \mid \text{basketball}) * P(\text{day} \mid \text{the}) \\ & * P(\text{before} \mid \text{day}) * P(\text{yesterday} \mid \text{before}) \end{aligned}$$

While the probability of “Xiaoming the day before yesterday played basketball” is

$$\begin{aligned} &P(\text{Xiaoming the day before yesterday played basketball}) \\ &= P(\text{Xiaoming} \mid \text{/start}) * P(\text{the} \mid \text{Xiaoming}) * P(\text{day} \mid \text{the}) \\ & * P(\text{before} \mid \text{day}) * P(\text{yesterday} \mid \text{before}) * P(\text{played} \mid \text{yesterday}) \\ & * P(\text{basketball} \mid \text{played}) \end{aligned}$$

Divide one probability by another:

$$\begin{aligned} &\frac{P(\text{Xiaoming the day before yesterday played basketball})}{P(\text{Xiaoming played basketball the day before yesterday})} \\ &= \frac{P(\text{the} \mid \text{Xiaoming}) * P(\text{played} \mid \text{yesterday})}{P(\text{played} \mid \text{Xiaoming}) * P(\text{the} \mid \text{basketball})} \end{aligned}$$

It is probably that the probability of the two sentences differs little in a word based LM, although they seem so different.

Some researchers have proposed their phrase based LM. Kuo and Reichl proposed a phrase based LM for SR which used an iteration to add new phrases in lexicon and to substitute the corpus with the new phrases, so as to reduce the word error rate (WER) and the perplexity.[1] Tang[2] used a similar method with Kuo and Reichl, they both

used bigram count and unigram log likelihood difference as their measure function. The difference is that Tang also used mutual information and entropy as his measure function, while Kuo and Reichl used bigram log likelihood difference and correlation coefficient instead. Heeman and Damnati proposed a different LM which derived the phrase probabilities from a language model built at the lexical level and lowered the WER.[3]

Table 1 generalized their works. Unfortunately, these methods are not specifically developed for the MT application, and they did not consider reordering which is what we focus on and will not occur in SR application.

Researcher	Kuo & Reichl	Tang	Heeman & Damnati
Area	SR	SR	SR
Content	LM using iteration to add phrases & substitute corpus with new phrases	LM using iteration to add phrases & substitute corpus with new phrases	LM in which probabilities of phrases are derived
Difference	use bigram log likelihood difference and correlation coefficient as measure function	use mutual information and entropy as his measure function	Phrase probability is derived
Result	WER & perplexity lower	Character & sentence accuracy higher, perplexity lower	WER lower

In the rest of paper, we propose two phrase based LMs in which phrases are taken into account rather than words. We describe how these LMs are made up and what the probability and perplexity of a sentence should be in these LMs.

The experiments on IWSLT data show that our LMs outperform the standard word based LM with the respect of perplexity and n-best list reranking.

## 2 Review of the Word Based LM

### 2.1 Sentence probability

In standard word based LM, probability of a sentence is defined as the product of each

word given its history. Probability of a sentence  $w_1^m$  is

$$P(w_1^m) = \prod_{i=2}^m P(w_i | w_1^{i-1}) * P(w_1)$$

If we approximate  $P(w_i | w_1^{i-1})$  to  $P(w_i | w_{i-n+1}^{i-1})$  ( $i-n+1 \geq 1$ ), we will have

$$P(w_1^m) \approx \prod_{i=n}^m P(w_i | w_{i-n+1}^{i-1}) * \prod_{i=2}^{n-1} P(w_i | w_1^{i-1}) * P(w_1)$$

This is the n-gram model.

## 2.2 Perplexity

A sentence's perplexity is defined as

$$PPL(w_1^m) = P(w_1^m)^{-\frac{1}{m}}$$

A text's perplexity is defined as

$$PPL(s_1^t) = \left( \prod_{i=1}^t P(s_i) \right)^{-\frac{1}{N}}$$

where  $s_i$  is the  $i$ -th sentence of the text and  $N$  is the total word number of  $s_1^t$ .

## 2.3 Smoothing

Generally, the probability of an n-gram is estimated as

$$P(w_i | w_{i-n+1}^{i-1}) = \frac{C(w_{i-n+1}^i)}{C(w_{i-n+1}^{i-1})}$$

where  $C(w_{i-n+1}^i)$  is the count of  $w_{i-n+1}^i$  that appeared in the corpus. But if  $w_{i-n+1}^i$  is unseen,  $P(w_i | w_{i-n+1}^{i-1})$  will be 0, so that any sentence that includes  $w_{i-n+1}^i$  will be assigned probability 0.

To avoid this phenomenon, Good-Turing smoothing is introduced to adjust counts  $r$  to expected counts  $r^*$  with formula

$$r^* = (r + 1) \frac{N_{r+1}}{N_r}$$

where  $N_r$  is the number of n-grams that occur exactly  $r$  times in corpus, and we

define  $N_0 = \sum_{i=1}^{\infty} i * N_i$ .

Furthermore, a back-off model is introduced along with Good-Turing smoothing to deal with unseen n-grams:

$$P_{BO}(w_i | w_{i-n+1}^{i-1}) = \begin{cases} \alpha(w_i | w_{i-n+1}^{i-1}) & \text{if } C(w_{i-n+1}^i) > 0 \\ d(w_{i-n+1}^{i-1})P_{BO}(w_i | w_{i-n+2}^{i-1}) & \text{else} \end{cases}$$

where

$$\alpha(w_i | w_{i-n+1}^{i-1}) = \frac{C^*(w_{i-n+1}^i)}{C(w_{i-n+1}^{i-1})}$$

and

$$d(w_{i-n+1}^{i-1}) = 1 - \sum_{w_i} \alpha(w_i | w_{i-n+1}^{i-1})$$

where  $C^*(w_{i-n+1}^i)$  is the adjusted count of  $w_{i-n+1}^i$  after Good-Turing smoothing.

## 3 Phrase Based LM

### 3.1 Model description

There are two phrase based LMs for us to propose. Both of them are based on probabilities of phrases, with the same estimation

$$P(p_i | p_{i-n+1}^{i-1}) = \frac{C(p_{i-n+1}^i)}{C(p_{i-n+1}^{i-1})}$$

We consider only phrases that has at most  $MPL$  words, in our models,  $MPL=3$ .

Given a sentence  $w_1^m$ , there are  $K$  segmentations  $S_1^K$  that satisfy the  $MPL$  limit, and the  $i$ -th segmentation  $S_i$  divides the sentence into  $J_i$  phrases. In our models, we consider a single word also as a phrase.

#### (1) Sentence probability

The probability of a sentence in the first model (sum model) is defined as

$$P(w_1^m) = \sum_{i=1}^K P(w_1^m, S_i) = \sum_{i=1}^K P(p_1^{j_i}, S_i) = \sum_{i=1}^K P(p_1^{j_i} | S_i) * P(S_i)$$

$$\approx \sum_{i=1}^K \prod_{j=1}^{j_i} P(p_j | p_{j-n+1}^{j-1}) * P(S_i)$$

$$\text{where } P(p_j | p_{j-n+1}^{j-1}) = \begin{cases} P(p_j | p_{j-n+1}^{j-1}) & \text{if } j \geq n \\ P(p_j | p_1^{j-1}) & \text{if } 1 < j < n \\ P(p_1) & \text{if } j = 1 \end{cases} \text{ and } P(S_i) = \frac{1}{K}.$$

The sentence probability formula of the second model (max model) is defined as

$$P(w_1^m) = \sum_{i=1}^K P(w_1^m, S_i) = \sum_{i=1}^K P(p_1^{j_i}, S_i) \approx P(p_1^{j_{i_0}}, S_i) = \prod_{j=1}^{j_{i_0}} P(p_j | p_{j-n+1}^{j-1})$$

where

$$i_0 = \underset{i}{\operatorname{argmin}} \operatorname{PPL}(w_1^m, S_i)$$

and  $P(p_j | p_{j-n+1}^{j-1})$  is same with that in sum model. The definition of  $\operatorname{PPL}(w_1^m, S_i)$  can be seen below.

## (2) Perplexity

Sentence perplexity and text perplexity in sum model use the same definition as that in word based LM.

Sentence perplexity in max model is defined as

$$\operatorname{PPL}(w_1^m, S_i) = P(w_1^m, S_i)^{-\frac{1}{j_i}}$$

and

$$\operatorname{PPL}(w_1^m) = P(w_1^m)^{-\frac{1}{j_{i_0}}}$$

where

$$i_0 = \underset{i}{\operatorname{argmin}} \operatorname{PPL}(w_1^m, S_i)$$

Text perplexity in max model is defined as

$$\operatorname{PPL}(s_1^t) = \left( \prod_{i=1}^t P(s_i) \right)^{-\frac{1}{N_0}}$$

where  $N_0 = \sum_{j=1}^t \operatorname{argmax}_i P(w_1^m, S_i, s_j)$ .



### (3) Smoothing

In phrase level, both models take back-off model along with Good-Turing smoothing, simply substituting  $w_i^j$  to  $p_i^j$  in the formulas. Moreover, we introduce an interpolation between phrase probability and product of single word probability:

$$P^*(p_j | p_{j-n+1}^{j-1}) = \lambda P(p_j | p_{j-n+1}^{j-1}) + (1 - \lambda) \frac{\prod_{i=1}^k P(w_i)}{(\sum_{\text{single word } w} P(w))^k}$$

where phrase  $p_j$  is made up of  $k$  words  $w_1^k$ . The idea of this interpolation is to make the probability of a phrase made up of  $k$  words smooth with a  $k$ -word unigram probability. In our experiments,  $\lambda = 0.43$ .

## 3.2 Algorithm of training the LM

Given a training corpus, our goal is to train a phrase based LM, i.e. to calculate  $C(p_i^j)$  for all  $p_i^j$  that  $0 \leq j - i \leq \text{maxorder} - 1$ . Therefore, for each sentence  $w_1^m$ , we should find out every  $k$ -grams that  $0 \leq k \leq \text{maxorder} - 1$ .

Any  $k$ -gram  $p_i^{i+k-1}$  can be described with  $k+1$  integers  $0 \leq b[0] < b[1] < \dots < b[k] \leq m$ , indicating that the first phrase is made up from word  $b[0]+1$  to word  $b[1]$ , the second phrase from  $b[1]+1$  to  $b[2]$  ... the  $k$ -th phrase from  $b[k-1]+1$  to  $b[k]$ , and  $b[i] - b[i - 1] \leq \text{MPL}$  for all  $i$ . Moreover, any  $(k+1)$ -tuple satisfying the requests above corresponds with a  $p_i^{i+k-1}$ . Therefore, we only need to exhaust all the  $k$ -tuples satisfying the requests above, and that just takes an iteration procedure. The Algorithm is in Table 2.

Table 2: Algorithm of Training the LM

Input: training corpus  $s_1^t$

Output: LM based on  $s_1^t$

procedure main

for each sentence  $w_1^m$  in  $s_1^t$

$b[i] \leftarrow 0$  for all  $i$

    for  $b[0]=0$  to  $m-1$  do

        iter(1)

Use the n-gram counts to train LM

procedure iter(order)

if  $order \leq \maxorder$  then do all the things below

    for  $j=b[order-1]+1$  to  $\min(b[order-1]+MPL, n)$  do

$b[order] \leftarrow j$

        Output the *order*-gram corresponding with  $b_0^{order}$

        iter( $order+1$ )

### 3.3 Algorithm of calculating sentence probability and perplexity

Given a sentence  $w$  and phrase based LM (sum model or max model), it is easy to make an algorithm following the formula. The algorithms both for sum model and for max model are shown below in Table 3(1) and Table 3(2).

Table 3(1): Probability & Perplexity in sum model

Input: sentence  $w_1^m$ , the sum model

Output: probability & perplexity of  $w_1^m$

sum  $\leftarrow 0$

for all K segmentations of  $w_1^m$ :

$p \leftarrow$  product of  $P^*$

    sum +=  $p$

sum /= K

probability = sum

perplexity =  $\text{sum}^{-1/m}$

Table 3(2): Probability & Perplexity in max model

Input: sentence  $w_1^m$ , the sum model

Output: probability & perplexity of  $w_1^m$

max  $\leftarrow 0$

for all K segmentations  $S_i$  of  $w_1^m$ :

$p \leftarrow$  product of  $P^*$

    if  $p > \max \{ \max \leftarrow p; \text{argmax} \leftarrow i \}$

probability  $\leftarrow$  max

$m_0 \leftarrow J_{\text{argmax}}$

perplexity =  $\text{sum}^{-1/m_0}$

## 4 Experiments

We performed experiments using our phrase based models, both sum model and max model, on a large and a small data track. We evaluated performance by measuring perplexity and BLEU (Papineni et al., 2002)[4].

### 4.1 Task 1: Small Track IWSLT

We first report the experiments using our phrase based models on the IWSLT data (IWSLT, 2011). Because of the computational requirements, we only employed the models on sentences which contain no more than 8 words.

We took general word based LM described in Chapter 2 as a baseline method (Base).

As shown in Table 4, the training corpus in English contains nearly 21 thousand sentences and 146 thousand words.

Data	Sentences.	Words	Vocabulary
Training	20997	145918	11906
Test	1000	6965	1672

The resulting systems were evaluated on the test corpus, which contains 1000 sentences. We calculated the perplexities of the test corpus with different upper limits of order using both sum model and max model, with and without smoothing described in Chapter 3.

We show the results measured in perplexity only. As shown in Table 5, the perplexities in sum models, with and without smoothing, are lower than that in Base.

The perplexities in max models are higher, probably because the formula of perplexity in max model is different.

Limit	Word(Base)	Sum	Sum Smoo.	Max	Max Smoo.
Unigram	287.04	67.89	89.05	475.47	705.11
Bigram	96.14	43.26	58.75	138.20	230.08
Trigram	89.91	43.33	58.94	125.60	210.14
4-gram	90.39	43.42	59.02	127.24	212.55
5-gram	90.90	43.44	59.04	128.20	214.16
6-gram	90.98	43.45	59.04	128.50	214.56
7-gram	91.00	43.45	59.04	128.75	215.07
8-gram	91.01	43.45	59.04	128.67	214.85

## 4.2 Task 2: Large Track IWSLT

We evaluate our models on the IWSLT data using both models with and without smoothing. Also because of computational requirements, we only employed the models on sentences which contain no more than 15 words.

As shown in Table 6, the evaluations were done on Dev2010, on Tst2010 and on Tst2011 data. Because of computational requirements again, we only selected sentences which contain no more than 10 words, and we only considered 10 best translations of each sentence instead of 1000 bests. For convenience, we only list the statistics of the reference.

Data	Sentences	Words	Vocabulary
Training	54887	576778	23350
Dev2010	202	1887	636
Tst2010	247	2170	617
Tst2011	334	2916	765

The results are shown in Table 7. Max model along with smoothing outperforms the baseline method under all three sets. The BLEU score increases with 0.3 on Dev2010, 0.45 on Tst2010, and 0.22 on Tst2011.

Model	Dev2010	Tst2010	Tst2011
Base	11.26	13.10	15.05
Word	11.92	12.93	14.76
Sum	11.86	12.77	14.80
Sum+Smoothing	12.02	12.54	14.76
Max	11.61	12.99	15.34
Max+Smoothing	11.56	13.55	15.27

We compared the sentences which were chosen by max model with those chosen by baseline method. Table 8 shows two examples from the chosen sentences from the Tst2010 corpus. We list sentences chosen with the baseline method and in max model respectively, as well as the reference sentences. Our max model generates better selection results than the baseline method in these cases.

Table 8: Sentence selection outputs with baseline method and in max model
(a) Baseline: but we need a success
Max model: but we need a way to success .
Reference: we certainly need one to succeed .
(b) Baseline: there &apos;s a specific steps that
Max model: there &apos;s a specific steps .
Reference: there &apos;s step-by-step instructions on this .

## 5 Conclusions

We showed that a phrase based LM can improve the performance of MT systems. We presented two phrase based models which consider phrases as the basic components of a sentence. By calculating the counts of phrases we can estimate the probabilities of phrases, and by segmenting the sentence into phrases we can calculate its probability and perplexity. The experiment results not only showed the models' outperforming, but also gave us confidence to improve them.

## 6 Acknowledgement

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导师评语 (包括对论文的标题、摘要、引言、结论、参考文献等方面是否符合基本规范的评价)	<p>论文介绍了统计语言模型中基于短语的模型,并进行了对比。</p> <p>该模型与传统的统计模型中基于字的方法相比,能够更好地捕捉到句法信息,提高翻译质量,同时保持了简洁性。</p> <p>论文以较为清晰的逻辑为目标,针对翻译中在统计模型中的问题,进行了深入的分析和研究,并给出了清晰的结论,为后续研究提供了新的思路。</p> <p>论文在写作过程中,能够体现出一定的学术水平和独立思考的能力,实验结果令人满意,符合培养目标,建议在进一步的研究中。</p>				
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