Improving SMT by Model Filtering and Phrase Embedding

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Outline

1. Introduction
2. Diverse Features for SMT Model Pruning
3. Bilingually-constrained Phrase Embedding
4. Conclusion

1. Introduction

- The Chinese-English SLT system jointly developed by Alex's team and my group was successfully demonstrated in Beijing Inter. Exhibition of Sci. & Tech., May 22-26, 2004, and in Barcelona Inter. Culture Forum, July 16-18, 2004.

- Intelligent terminals have become increasingly popular

1. Introduction

- The problem of pruning the translation model for a statistical machine translation (SMT) system
  - Phrase-based MT model (PBTM)
  - Hierarchical phrase-based translation model (HPBTM)

How to choose the most promising translation candidates from a large-scale translation table with several conditional probabilities?

1. Introduction

- How to distinguish the phrases with different semantic meanings?

  - Proposed a Bilingually-constrained Recursive Auto-encoders (BRAE) to learn semantic phrase embeddings (compact vector representations for phrases).

Outline

1. Introduction
2. **Diverse Features for SMT Model Pruning**
3. Bilingually-constrained Phrase Embedding
4. Conclusion

2. Diverse Features for SMT Model Pruning

- The translation pairs are extracted by a heuristic method based on the word alignments learned from parallel corpora

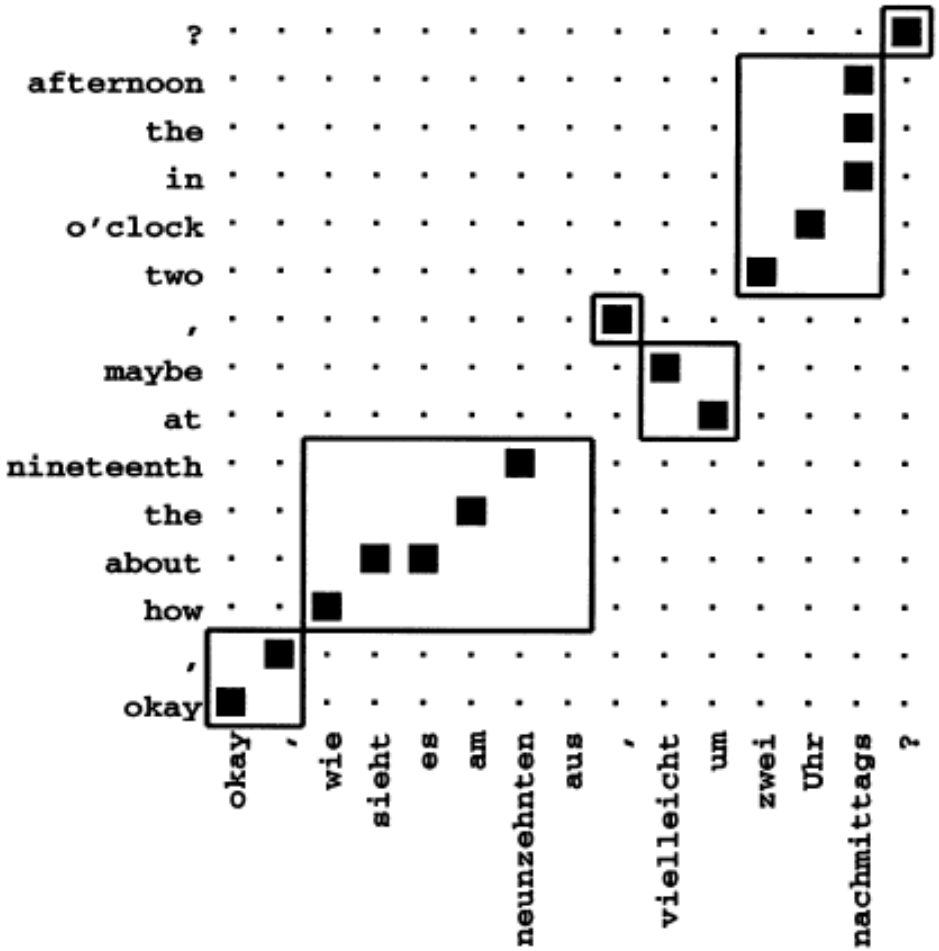


Fig. 1 The translation pairs [Och and Ney, 2004]

2. Diverse Features for SMT Model Pruning

- Generally, two typical sorts of phrase-pairs cause the phrase table to be redundant and much larger than expected

  - One is that a distinct source phrase corresponds to many translation options (1-to-many).

大量 ||| a big amount of
大量 ||| a big amount
大量 ||| a big way
大量 ||| a big
大量 ||| a charter flight
大量 ||| a chernobyl
大量 ||| a large number
大量 ||| a considerable amount of
大量 ||| a considerable quantity of
大量 ||| a deeper level
大量 ||| a decrease in
大量 ||| a drink
大量 ||| a large sum of
大量 ||| a survival

2. Diverse Features for SMT Model Pruning

- The other case is that a distinct source phrase has only one or two translation options (1-to-few)

! - * * 内容 ||| is to do his
! 神人 俱 以 证之， 世世代代 ||| han
冷血 动物 ||| cool blooded animal
" 十五 " 计划 ||| the 10th five-year plan
并 不见得 永远 ||| is not always
徐明阳 ||| autonomous regional cpc
一 名 光荣 ||| a glorious
友好 的 柬埔寨 ||| friendly cambodian
双边 磋商 取得 实效， ||| it
口 人 在一起 才 ||| only living
口惠 ||| just paying
口惠 ||| noting
口风 ||| his tone
口风 ||| revealed his intention

2. Diverse Features for SMT Model Pruning

- Some existing pruning methods
  - Use heuristic rules to cut off overloaded translation options

Those methods always do not work for the second case (1-to-few).

  - Some methods adopt Fisher's significance test to prune the weakly associated pairs

2. Diverse Features for SMT Model Pruning

Fisher's significance test

Given a training set that contains *N* parallel sentences and a phrase-pair (*s*, *t*) to be valued, we need to collect *C*(*s*), *C*(*t*) and *C*(*s*, *t*), which represent the counts of sentences that contain *s*, *t* and the pair (*s*, *t*), respectively.

The probability that the pair (*s*, *t*) occurs times by chance is given by the hyper-geometric distribution, as follows

$$P_h\big(c(s), c(t), c(s,t)\big) = \frac{\binom{c(s)}{c(s,t)} \times \binom{N-c(s)}{c(t)-c(s,t)}}{\binom{N}{c(t)}}$$

2. Diverse Features for SMT Model Pruning

The corresponding *p*-value is the sum of $P_v(C(s', t'))$ under the circumstance that $C(s', t')$ is not less than $C(s, t)$, while $C(s')$ equals $C(s)$ and $C(t')$ equals $C(t')$,

$$P_v(c(s), c(t), c(s,t)) = \sum_{\substack{c(s\prime,t\prime)>=c(s,t) \\ c(s\prime)=c(s) \\ c(t')=c(t)}} P_h(c(s'), c(t'), c(s', t'))$$

If two phrase pairs occur the same times, and their source sides and target sides have the same times, their *p*-value is same.

If the *p*-value of a phrase pair is less than a threshold value, it will be ignored.

2. Diverse Features for SMT Model Pruning

- Some methods adopt Fisher's significance test to prune the weakly associated pairs

However, they may discard many useful pairs unexpectedly, such as named entities that occur rarely in a parallel training corpus, which could damage the translation quality.

- Other methods using relative entropy are good at pruning redundant phrases, especially for those long phrases that can be replaced by combining shorter phrases

But the score of combined phrases often differs from the original one.

2. Diverse Features for SMT Model Pruning

- **Our motivations**
  - We consider the pruning task as a classification problem
  - Many effective heuristic measures mentioned above are encoded as strong representative features under the classification framework

We have explored rich statistical and syntactic features that are applied to the classification framework to compact the translation tables of PBTM and HPBTM as much as possible.

2. Diverse Features for SMT Model Pruning

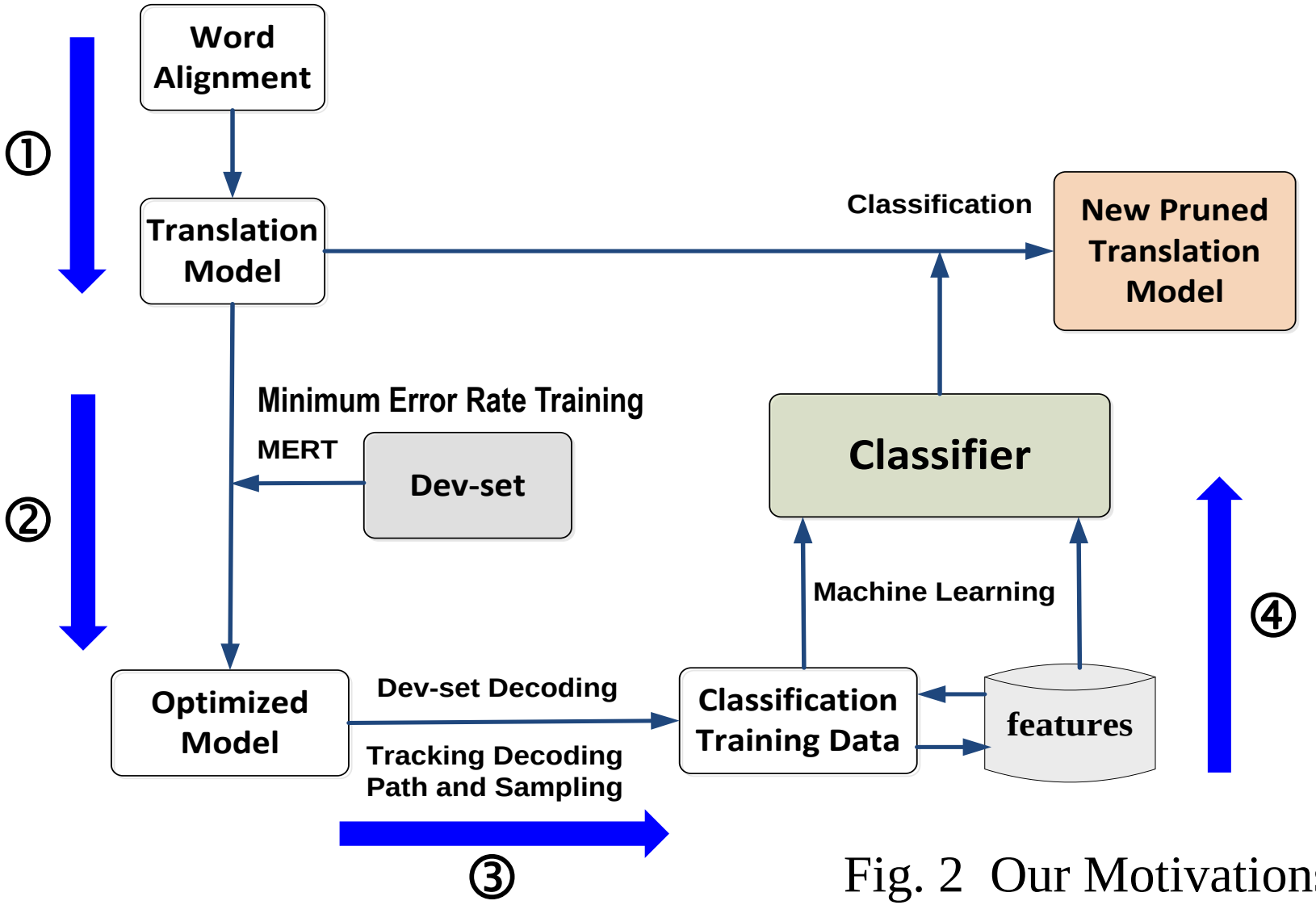


Fig. 2 Our Motivations

2. Diverse Features for SMT Model Pruning

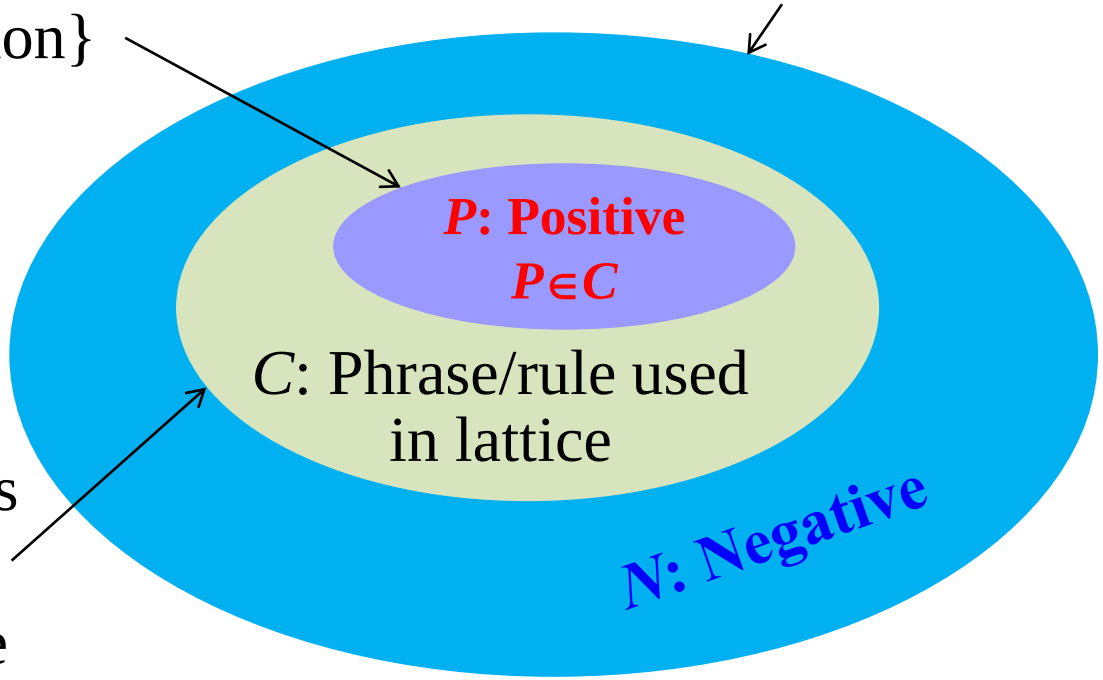
- **Some details of the methods**

  (1) Training set for the classifier

P = {Phrase pairs or rules truly used in the final translation}

P is a sub-set of *C*.

W = {Dev-phrase or Dev-rule}



C = {Phrase pairs or rules that have been involved into the translation lattice once or more}

Fig. 3 Different Sets

2. Diverse Features for SMT Model Pruning

(2) Four types of features for pruning the phrase-based models

- Bi-directional phrase translation probabilities and bi-directional lexicalized translation probabilities
- Reordering probabilities
- Syntactic constraints on source side

不是什么 ||| **is not a**

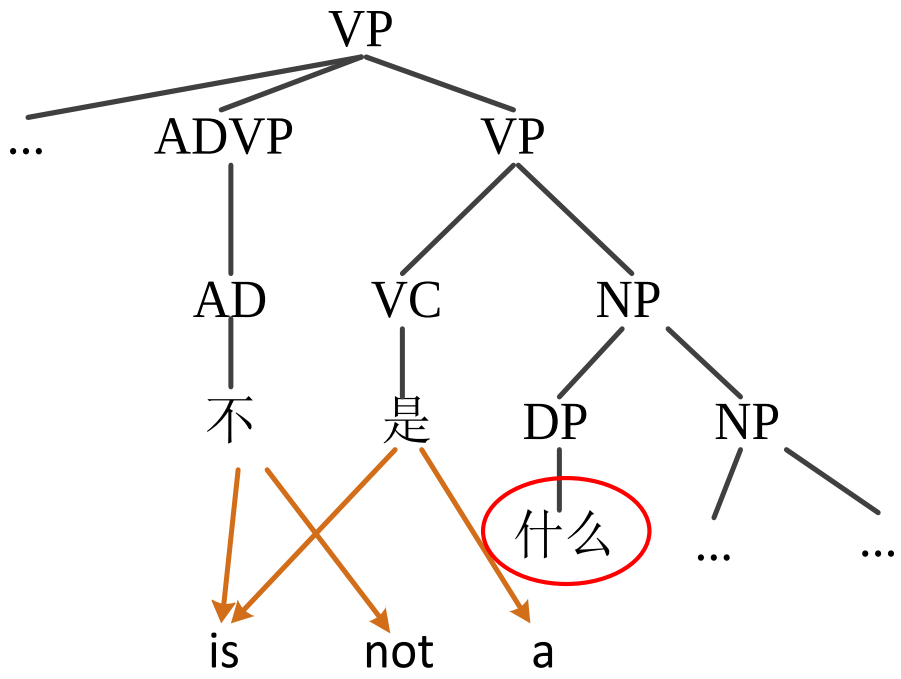
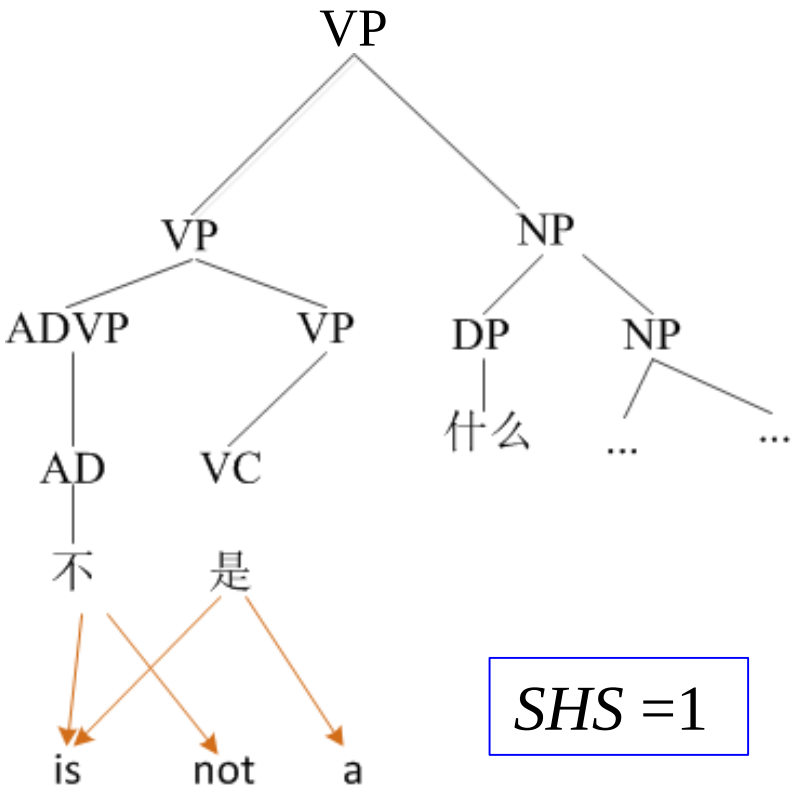


Fig. 4

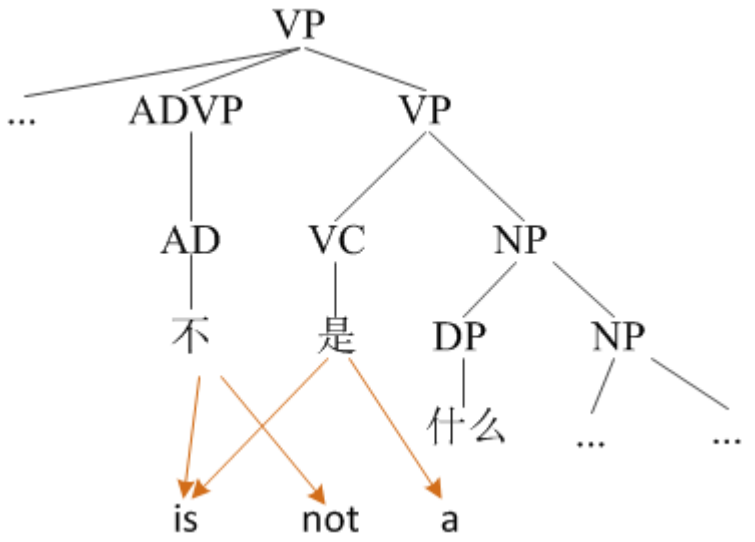
2. Diverse Features for SMT Model Pruning

The source syntactic constraint features are listed as follows:

- ✓ *SHS*: if the source phrase starts with a syntactic sub-phrase (more than one word), then *SHS*=1, otherwise, *SHS*=0;



SHS =1

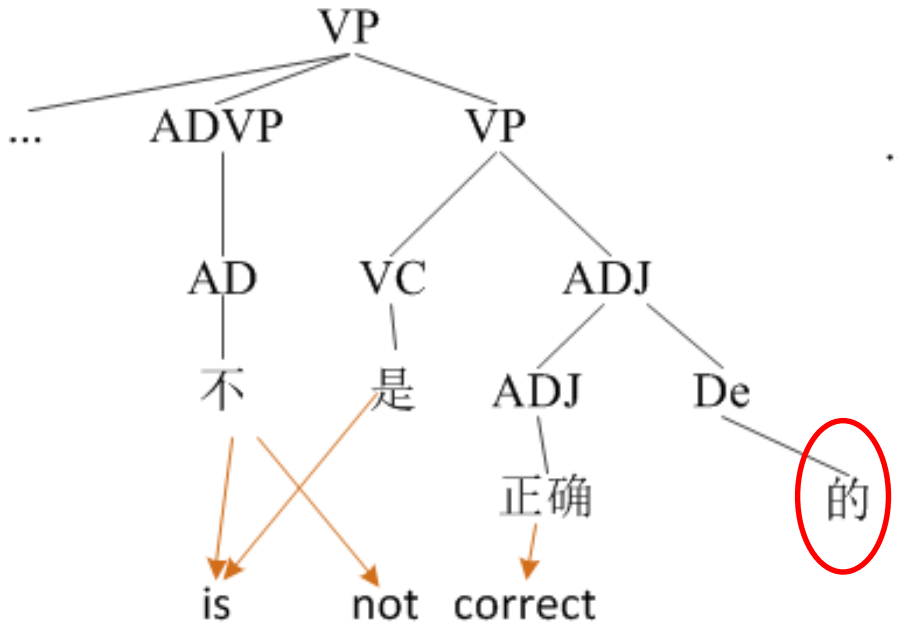


SHS =0

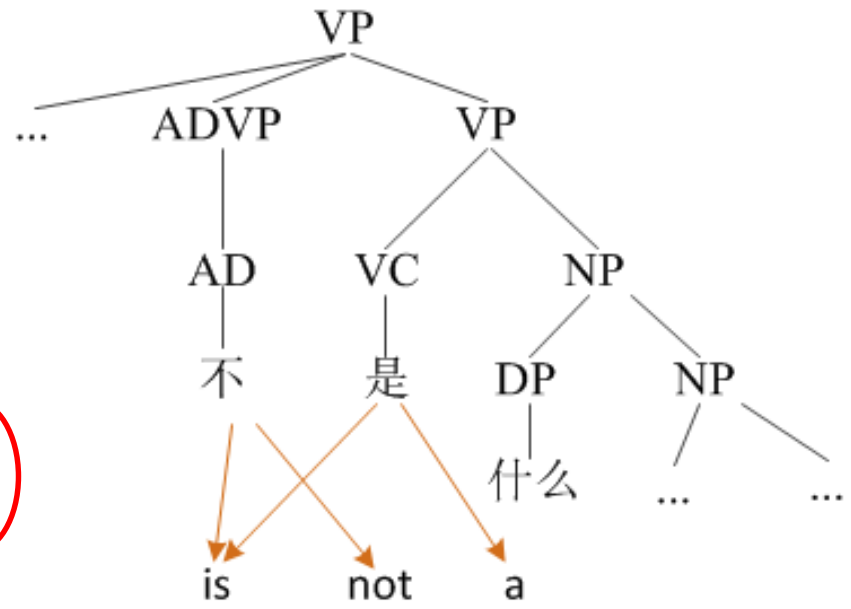
Fig. 5

2. Diverse Features for SMT Model Pruning

- ✓ *STS*: if the source phrase ends with a syntactic sub-phrase (more than one word), then *STS*=1; otherwise, *STS*=0;



STS =1

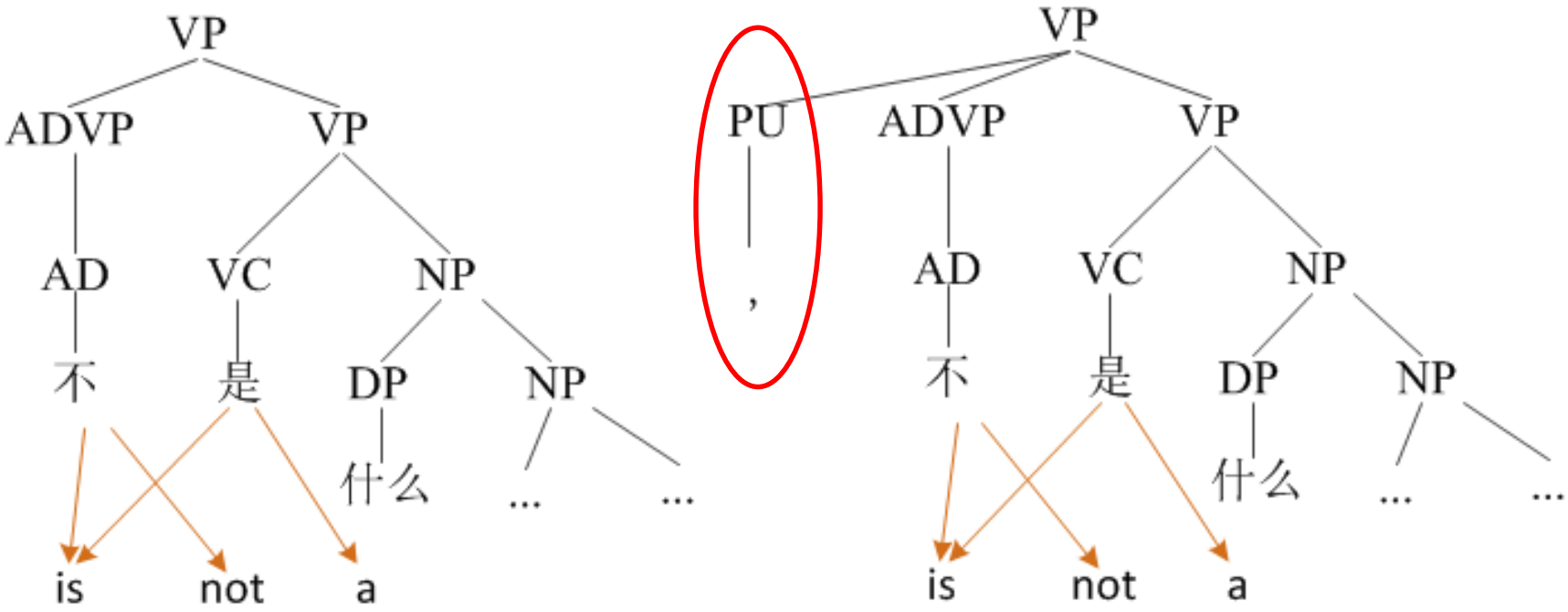


STS =0

Fig. 6

2. Diverse Features for SMT Model Pruning

- ✓ *SHA*: if the first word of the source phrase is aligned, then *SHA*=1; otherwise, *SHA*=0;



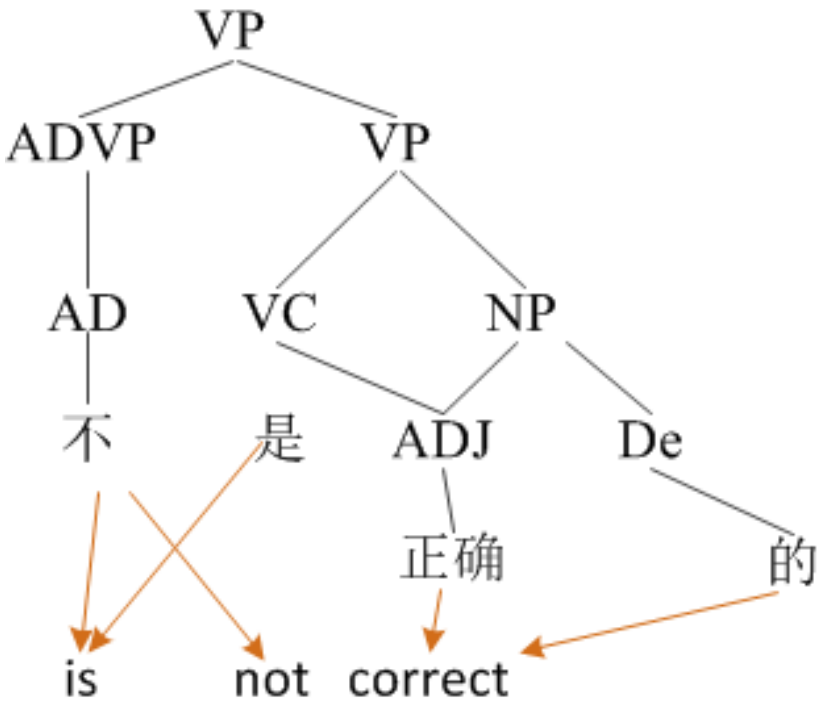
SHA =1

SHA =0

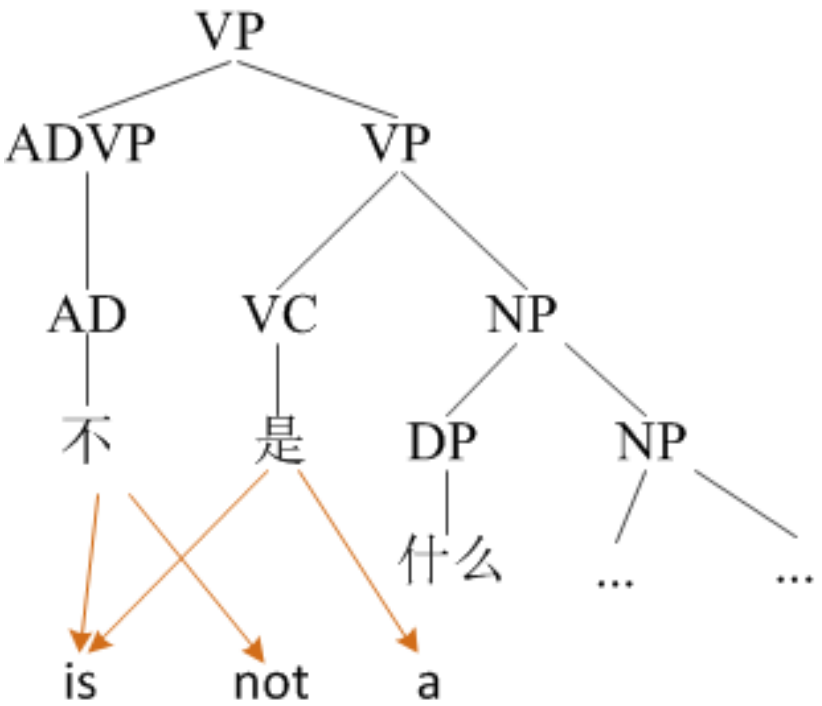
Fig. 7

2. Diverse Features for SMT Model Pruning

- ✓ *STA*: if the last word of the source phrase is aligned, then *STA*=1; otherwise, *STA*=0;



STA =1



STA =0

Fig. 8

2. Diverse Features for SMT Model Pruning

✓ *SSW*: if the source phrase is a single word, then *SSW*=1; otherwise, *SSW*=0;

大量 ||| a big amount of

SSW =1

友好 的 柬埔寨 ||| friendly Cambodian

SSW=0

Binary values for phrase pair: 不 是 什么 ||| is not a

Table 1

Phrase Pair	不 是 什么 ||| is not a
SHS	0
STS	0
SHA	1
STA	0
SSW	0

The syntactic constraints on target side are the same as those of the source syntactic constraints.

2. Diverse Features for SMT Model Pruning

- *p*-value feature

  We add the length ratio as a feature. Let L_s be the length (the word count) of the source phrase, and let L_t be the length of the target phrase. Then

$$LenRatio = \min(L_s, L_t) / \max(L_s, L_t)$$

2. Diverse Features for SMT Model Pruning

(3) Features for pruning the hierarchical phrase-based models

In terms of the features for the rules with non-terminals, there are a total of three types:

- The rule translation probabilities and lexicalized translation probabilities
- LenRatio:

  $LenRatio = \min(L_{s\_terminal}, L_{t\_terminal}) / \max(L_{s\_terminal}, L_{t\_terminal})$

- Dependency syntactic features

  Relax-Well-Formed (RWF) structure (Z. Wang et al., 2010)

2. Diverse Features for SMT Model Pruning

Given a sentence $S = w_1 w_2 ... w_n$, and let $d_1 d_2 ... d_n$ represent the position of parent word for each word. If w_i is a root, then d_i=-1.

Given a dependency structure $w_i \ldots w_j$, it will be called a *Relax-Well-Formed* structure if and only if it satisfies the following conditions:

- $d_h \notin [i, j]$Z, where $h \notin [i, j]$
- $\forall k \in [i, j]$, $d_k \in [i, j]$ or $d_k = h$, where $h \notin [i, j]$

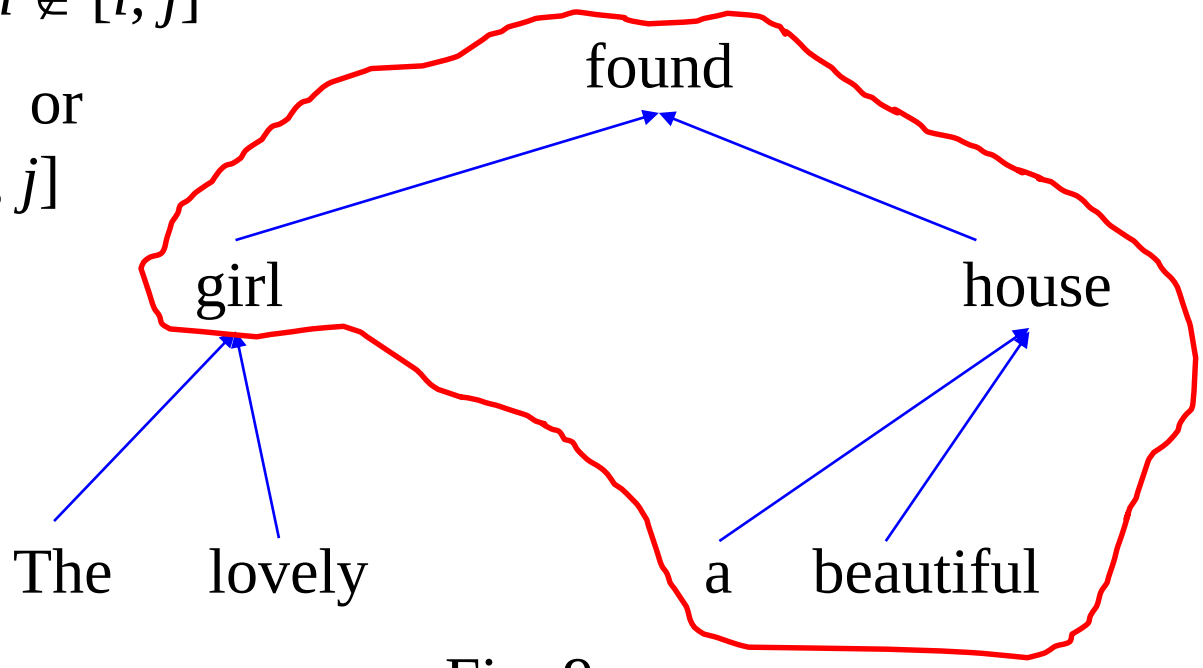


Fig. 9

2. Diverse Features for SMT Model Pruning

We say that *RWF*(rule) = true if a rule is *Relax-Well-Formed*.

Given a rule (r_l, r_r), we obtain the values in the triple vector (D_l, D_r, D_b) for r_l and r_r as follows,

$$D_l = \frac{\sum_{i \in S_s} I(RWF(r_{li}) = true)}{\sum_{i \in S_s} I(r_{li})}$$

D_l is the dependency feature value for the source side of a rule.

$$D_r = \frac{\sum_{j \in S_t} I(RWF(r_{rj}) = true)}{\sum_{j \in S_t} I(r_{rj})}$$

D_r is for the target side.

$$D_b = \frac{\sum_{i \in S_s} \sum_{j \in S_t} I(RWF(r_{li}) = true, RWF(r_{rj}) = true)}{\sum_{i \in S_s} \sum_{j \in S_t} I(r_{li}, r_{rj})}$$

D_b is for both sides.

2. Diverse Features for SMT Model Pruning

Summarization on our motivations

- Use the following diverse features
  - Bi-directional phrase translation probabilities and bi-directional lexicalized translation probabilities
  - Reordering probabilities
  - Syntactic constraints on source side
  - *p*-value feature
- Build an SVM-based classifier
  - Trained by the open toolkit LIBSVM
  - Chose Radial Basis Function (RBF) as our kernel function

2. Diverse Features for SMT Model Pruning

- Experiments
  - Experimental Setup
    - Training data: FBIS corpus, 7.1 million Chinese words and 9.2 million English words
    - Development set : NIST03, 919 sentences
      NIST04, 1,788 sentences
    - Test set: NIST05 and NIST06 are only used as testing data in the translation task and never used for training the classifier

2. Diverse Features for SMT Model Pruning

- To obtain the original phrase-based and hierarchical phrase-based translation model, we train a 5-gram language model with SRILM on the FBIS English part
- We obtain the source-to-target and target-to-source word alignments by GIZA++
- These alignments are then symmetrized with grow-diag-final-and strategy
- The translation model is generated by Moses (2010-8-13 Version), using the default parameter settings
- For the phrase-based translation model, the maximum length of the phrases in the phrase table is 7
- For pruning settings, the beam size is 200, and 20 translation options are retrieved for each input phrase

2. Diverse Features for SMT Model Pruning

The features contained in the baseline translation system:

- ✓ bi-directional phrase translation probabilities
- ✓ bi-directional lexicalized translation probabilities
- ✓ bidirectional standard lexicalized reordering probabilities
- ✓ phrase penalty, word penalty
- ✓ distance-based reordering model score
- ✓ language model

For the hierarchal phrase-based translation model, we use the same setup as the phrase-based model, except we limit the number of symbols on each side of a rule to 5.

2. Diverse Features for SMT Model Pruning

For the training data for the SVM-based classifier,

- 10,000 positive training data instances
- 10,000 negative training data instances.

Dependency syntactic features

- Berkeley parser
- Trained on the Penn Chinese Treebank 6.0

2. Diverse Features for SMT Model Pruning

- Results on the Phrase-Based Model

Table 2: Performance of the SVM-based Classifier

Combination of Features	Accuracy(%)
PLTP+LenRatio+PV	94.90
SS+TS	84.92
PLTP+LRP+LenRatio+PV	**95.81**
PLTP+LRP+LenRatio+TS+PV	94.98
PLTP+LRP+LenRatio+SS+TS+PV	93.26
PLTP+LRP+Lt/Ls+Ls/Lt+PV	95.06
PLTP+LRP+Lt/Ls+Ls/Lt+TS+PV	94.38

- PLTP: phrase and lexicalized phrase translation probabilities, bi-directional
- LRP: The standard lexicalized reordering probabilities; PV: *p*-value
- SS: Source syntactic features; TS: Target syntactic features
- Length of the target phrase (Lt); Ls: Length of the source phrase

2. Diverse Features for SMT Model Pruning

Table 3: Size and BLEU for different combined features compared the baseline (POS: NEG = 1:1)

	Table Size	NIST'05 BLEU	NIST'06 BLEU
Baseline	15,428,040	25.30	26.86
PLTP+LenRatio+PV	9,355,935(61%)	25.12	**26.98**
SS+TS	8,514,694(55%)	24.65	25.04
PLTP+LRP+LenRatio+PV	6,336,658(41%)	25.33	26.87
PLTP+LRP+LenRatio+TS+PV	**3,756,190(24%)**	25.26	26.73
PLTP+LRP+LenRatio+SS+TS+PV	6,584,166(43%)	25.25	26.87
PLTP+LRP+Ls/Lt+Lt/Ls+PV	5,569,328(36%)	25.34	26.76
PLTP+LRP+Ls/Lt+Lt/Ls+PV+TS	4,962,691(32%)	**25.40**	26.63

2. Diverse Features for SMT Model Pruning

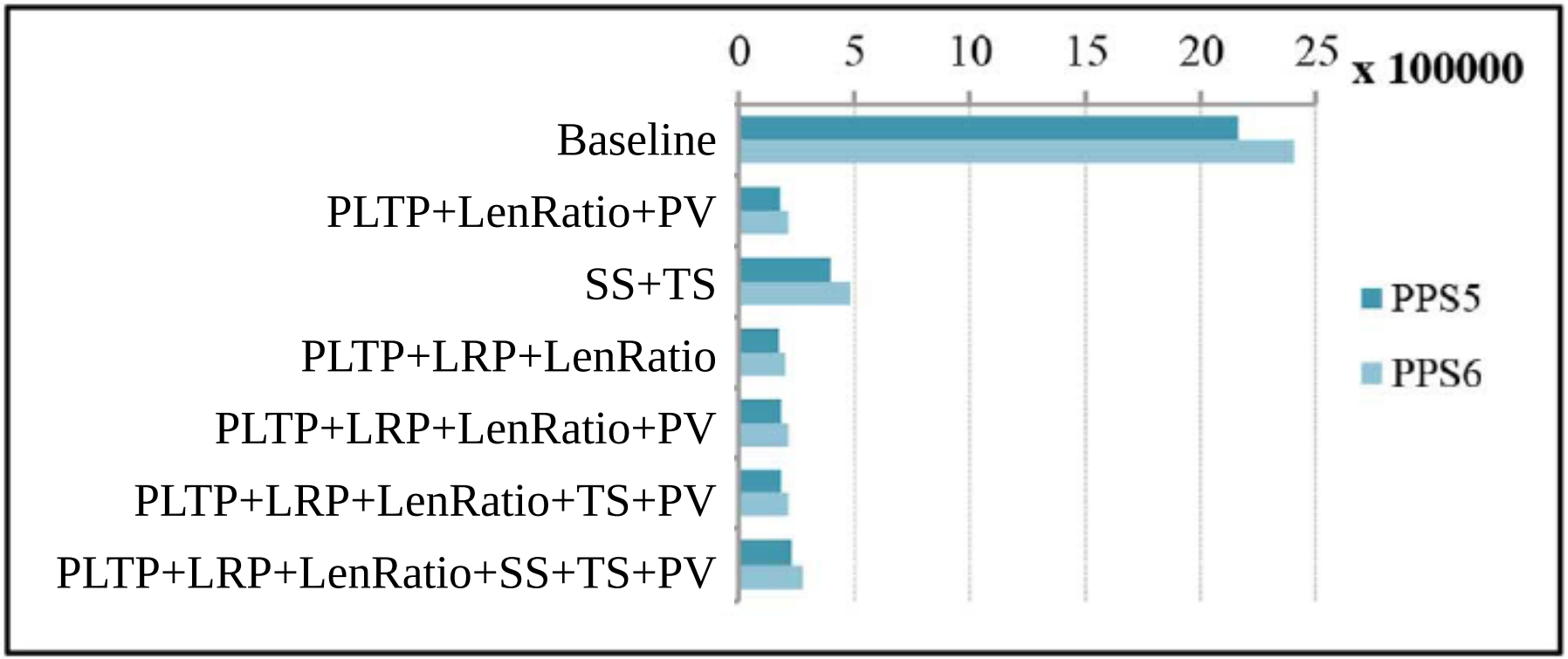


Fig. 10 Changes in the table size of NIST05 and NIST06

2. Diverse Features for SMT Model Pruning

Table 4: Basic Statistics of the Original and Pruned Phrase under the Features PLTP + LRP + LenRatio + TS + PV

	Whole Table		NIST05		NIST06	
	original	pruned	original	pruned	original	pruned
DSN	5,691,593	2,924,778	21,319	19,337	27,911	25,013
ACPS	2.71	1.28	101.5	9.429	86.2	8.52
ALS	4.17	4.04	2.157	2.108	2.23	2.18
ALT	4.02	3.68	3.41	2.12	3.41	2.14

DSN: distinct source phrase numbers;
ACPS: average candidate-options per distinct source phrase;
ALS: average length of distinct source phrases ;
ALT: average length of target phrases

2. Diverse Features for SMT Model Pruning

- Testing on a Different Scale of Negative Data

Table 5. BLEU score on the test set with an increasing rate of negative data

POS:NEG	NIST'05/'06	
	GROUP1	GROUP2
Baseline	25.30/26.86	
1:1.00	25.33/ 26.87	25.26 /26.73
1:2.00	25.40 / 26.75	25.28 / 26.63
1:3.00	25.44/ 26.63	25.37/ 26.47
1:4.00	25.48/ 26.59	25.32/ 26.39
1:5.00	25.37/ 26.56	25.40/ 26.31

- Group 1 of features: PLTP, LRP, LenRatio and PV
- Group 2 of features: Group 1 + TS

2. Diverse Features for SMT Model Pruning

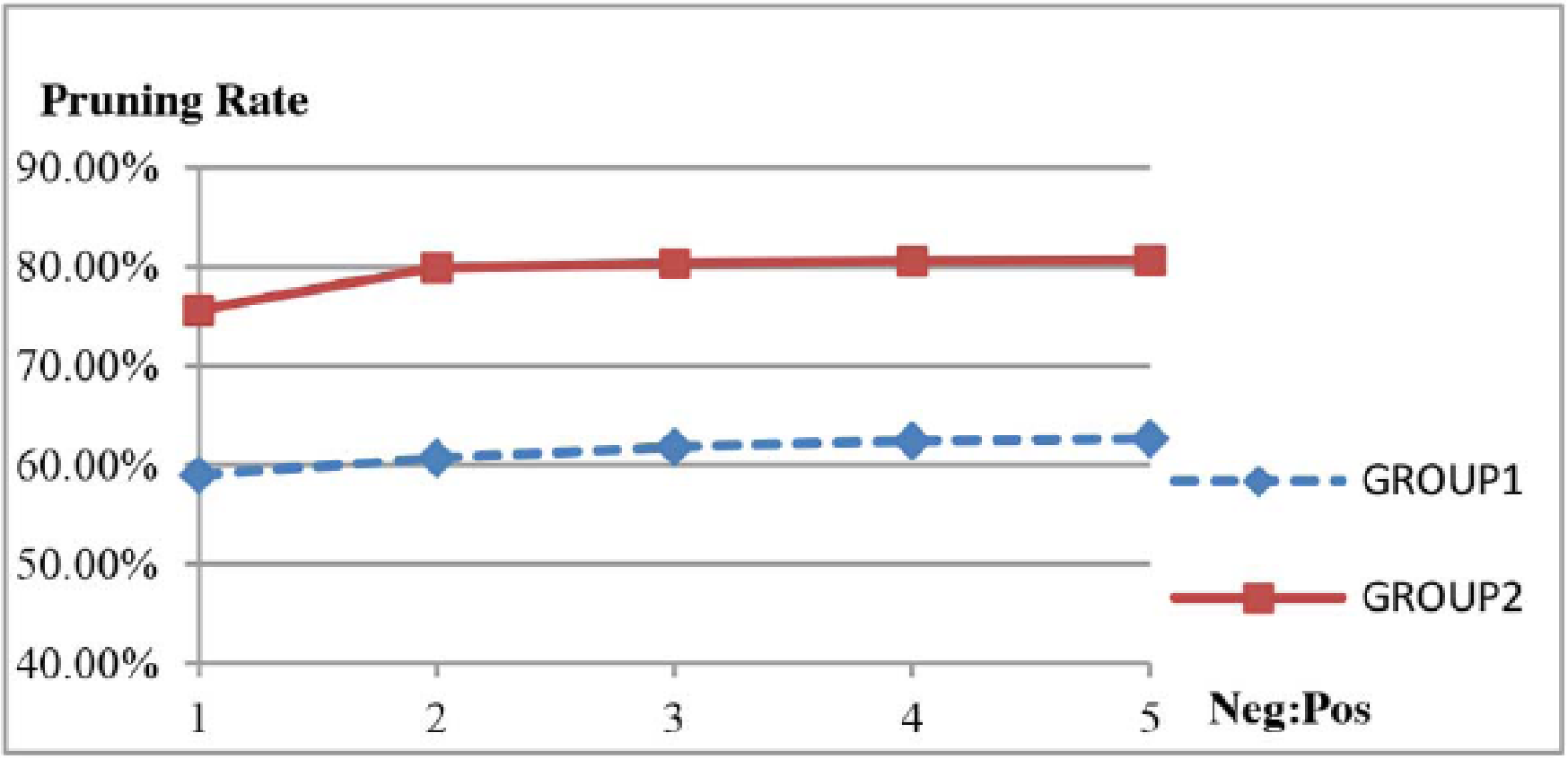


Fig. 11 The reduction in the whole table size

2. Diverse Features for SMT Model Pruning

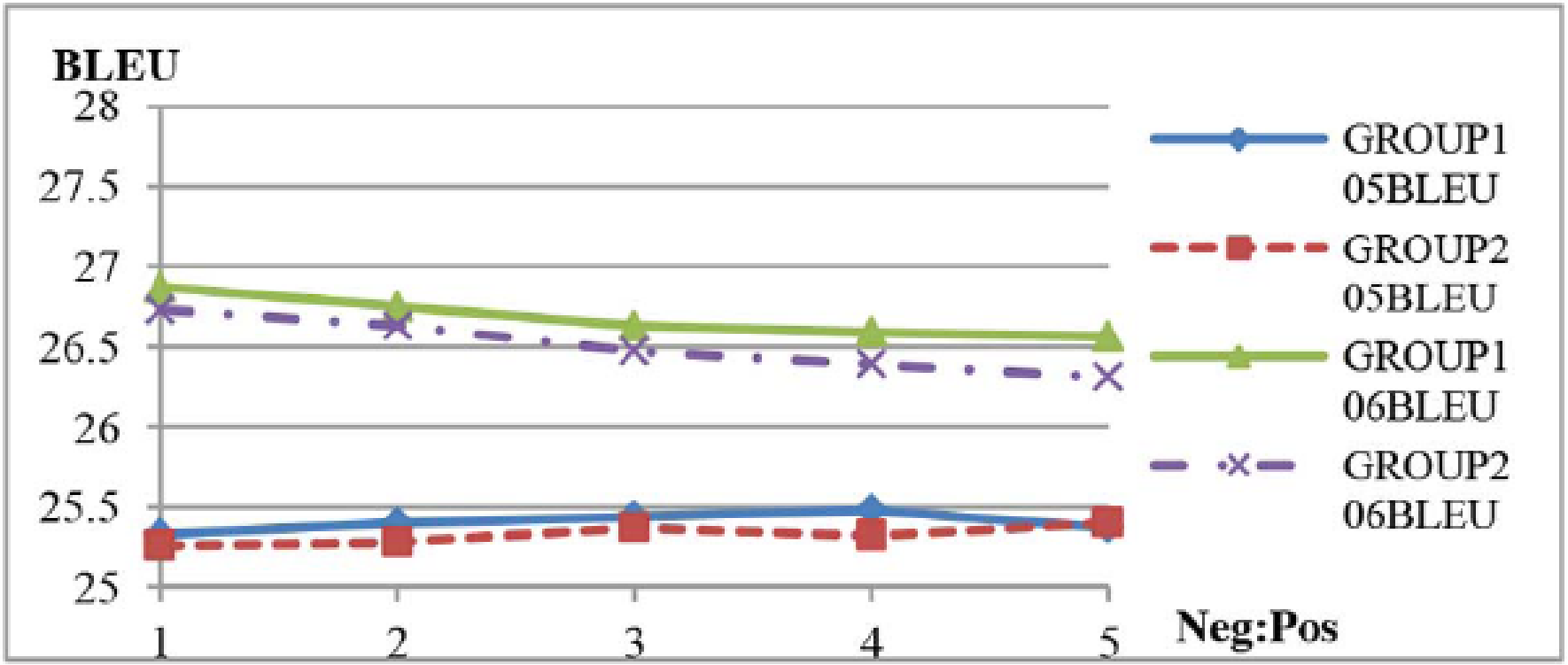


Fig. 12 The translation quality of the testing set with different ratios of negative and positive data

2. Diverse Features for SMT Model Pruning

- Results on the Hierarchical Phrase-Based Models

Table 6. Size and BLEU of different combined features in HPBTM

	Table Size	BLEU	
		NIST05	NIST06
Baseline	69,393,064(100%)	25.58	28.15
RWF	45,338,911(65%)	**25.91**	28.11
RLTP+PV+LenRatio	28,614,096 (41%)	25.73	28.00
RLTP+PV+LenRatio +DSS+DTS+DBOTH	24,954,654 (36%)	25.77	28.05
RLTP+PV+LenRatio +DTS+DBOTH	**23,126,972 (33%)**	25.69	**28.15**

- RWF: Relax-Well-Formed
- DSS: Dependency syntactic feature of source side
- DTS: Dependency syntactic feature of target side;
- DBOTH: Dependency syntactic feature of both sides

2. Diverse Features for SMT Model Pruning

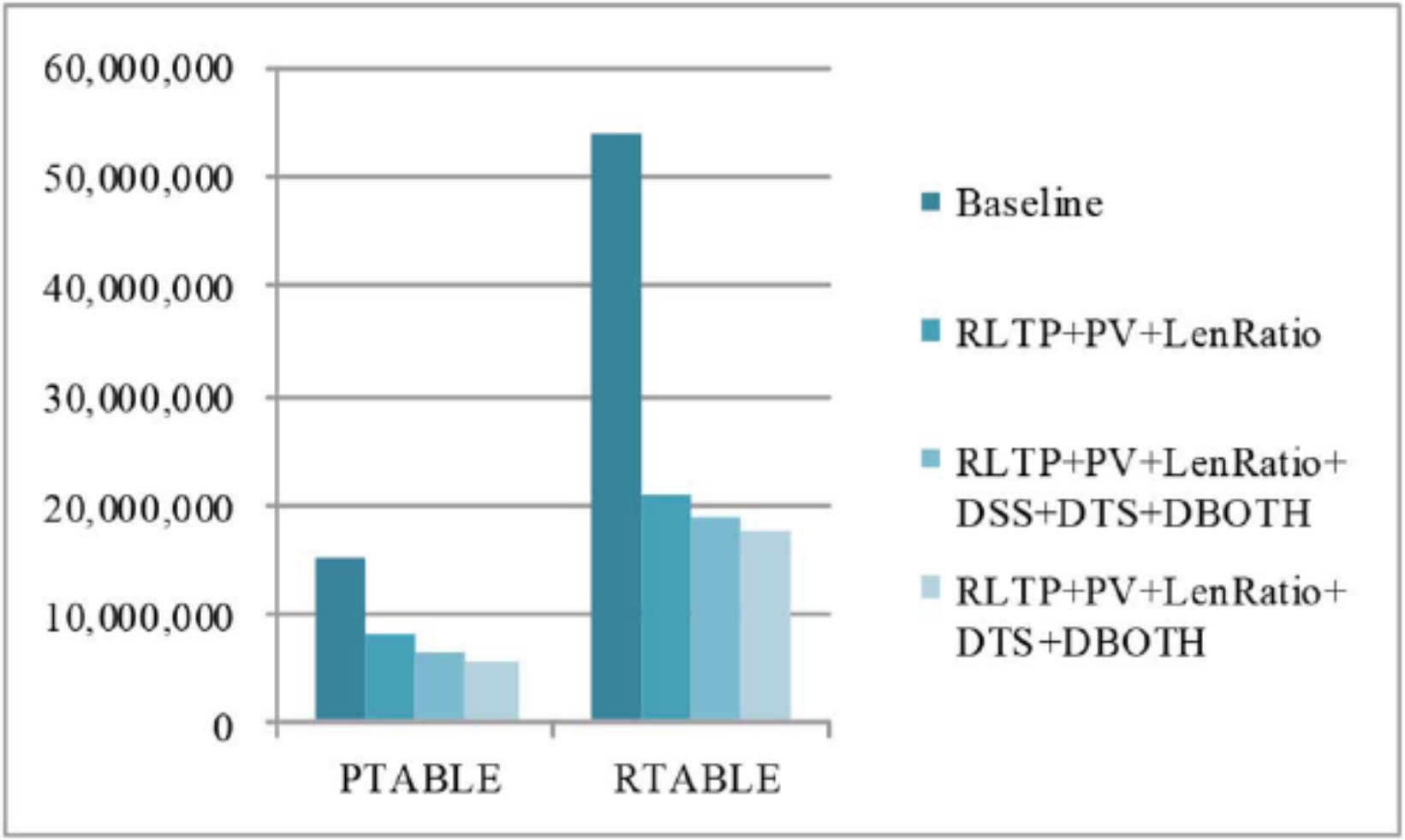


Fig. 13 Details of Phrase-table and Rule-table

2. Diverse Features for SMT Model Pruning

Table 6. Accuracy of Classifier with Different feature Combinations

	Accuracy	
	P-Classifier	R-Classifier
RLTP+PV+LenRatio	98.07%	95.99%
RLTP+PV+LenRatio+DSS+DTS+DBOTH	96.97%	95.24%
RLTP+PV+LenRatio+DTS+DBOTH	97.21%	95.42%

P-classifier is for the phrase-table; R-classifier is for the rule-table.

2. Diverse Features for SMT Model Pruning

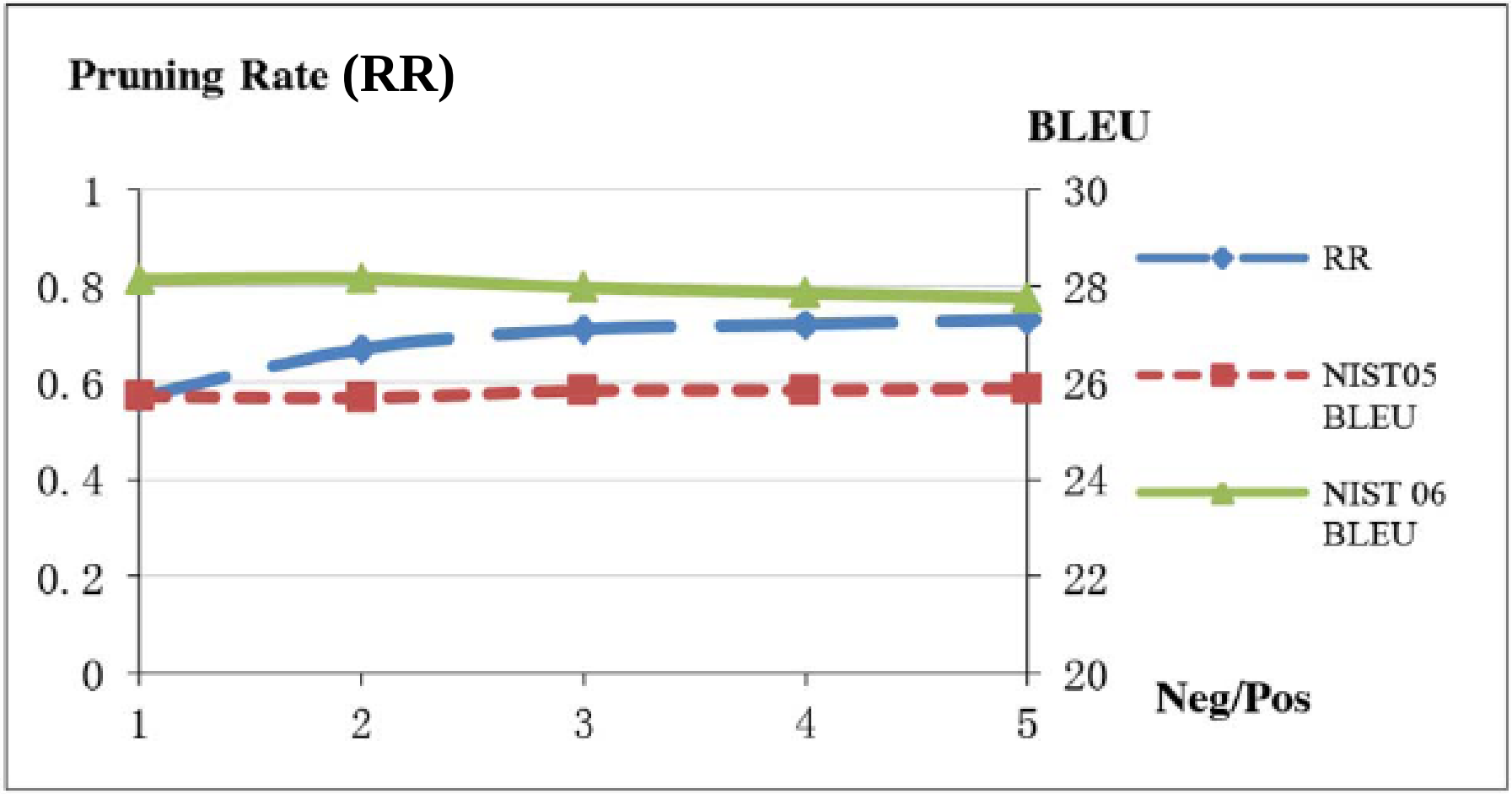


Fig. 14 The reduction in the whole table size with different scales of negative data in the hierarchical model

2. Diverse Features for SMT Model Pruning

- **Summarization on SMT model pruning**
  - The classifier-based approach is effective at pruning approximately 80% of the phrase-pairs and 70% of the rules without harming the translation quality
  - For the Chinese-to-English translation task, it is better not to use the source syntactic information as a single feature
  - Training data of the classifier are generated automatically from the decoding path with a tuned translation model and development data
  - Our unified framework breaks the limitation of specific translation model pruning, which makes it possible to extend and transfer to other syntactic translation models

2. Diverse Features for SMT Model Pruning

For more details about this work, please refer to:

M. Tu, Y. Zhou, and C. Zong, Exploring Diverse Features for Statistical Machine Translation Model Pruning, IEEE *Transactions on s on Audio, Speech and Language Processing*, Vol. 23, No. 11, Nov. 2015, pp. 1847-1857

Outline

1. Introduction
2. Diverse Features for SMT Model Pruning
3. **Bilingually-constrained Phrase Embedding**
4. Conclusion

3. Bilingually-constrained Phrase Embedding

Word Embedding:

Maps a word into a real-valued vector

meeting: [0.25, 0.12, 0.36]

conference: [0.24, 0.10, 0.35]

3. Bilingually-constrained Phrase Embedding

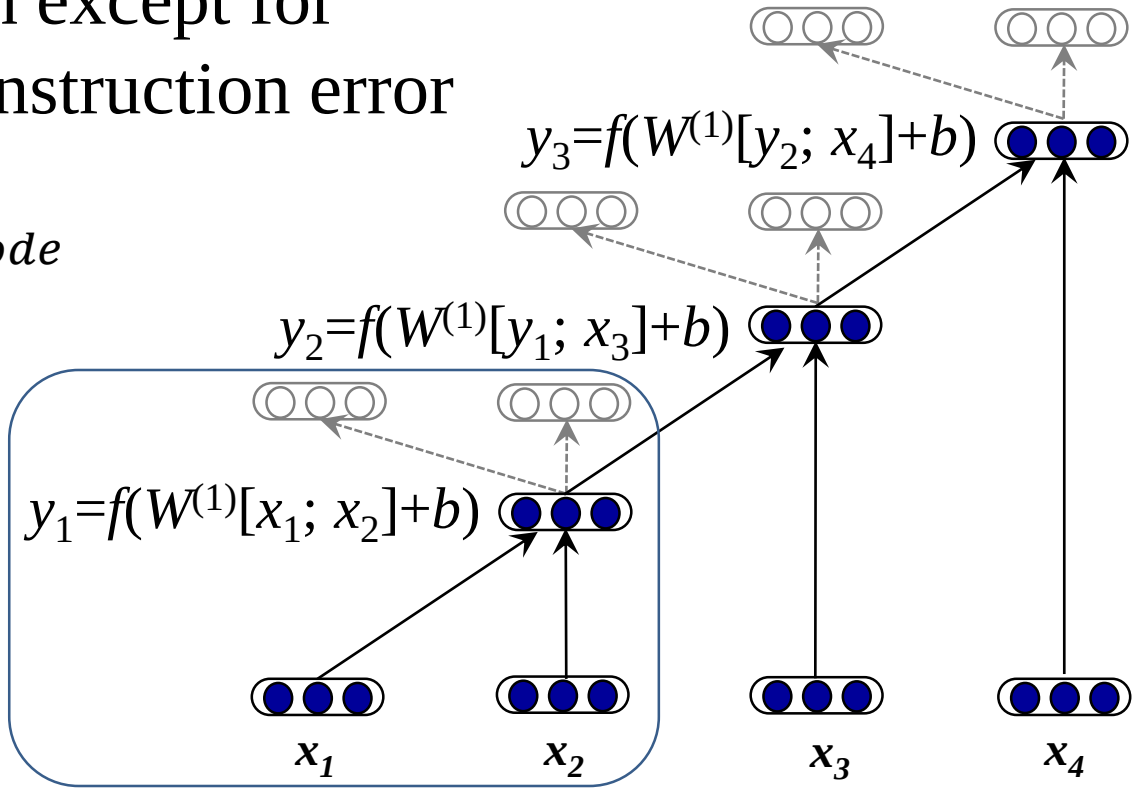
- View any phrase as a single unit, using the word embedding method
  - Context of a phrase is always limited
  - Cannot enumerate all the phrases
- View any phrase as bag-of-words
  - Sum of word embeddings
  - Ignore the word order information
- View any phrase as meaningful combination of words
  - Learn the way of combination
  - Apply recursive auto-encoders

3. Bilingually-constrained Phrase Embedding

- **Unsupervised Phrase Embedding with Recursive Auto-encoder (RAE)**

- No other supervision except for minimizing the reconstruction error

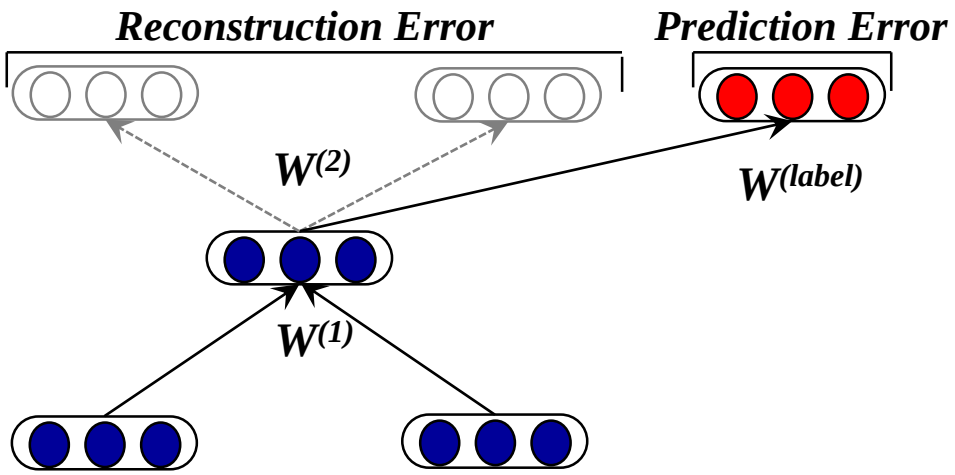
$$E_{total} = \sum_{node} E_{Rec\_node}$$



Unsupervised RAE can only learn some syntactic information of the phrase, but cannot learn the correct semantics

3. Bilingually-constrained Phrase Embedding

- **Semi-supervised Phrase Embedding**



$$E([x_1, x_2]) = \alpha E_{REC}([x_1, x_2]) + (1 - \alpha) E_{pE}(y)$$

Parsing: label is the **syntactic category**
Sentiment Analysis: label is the **polarity**
Phrase Reordering: label is the **swap or monotone**

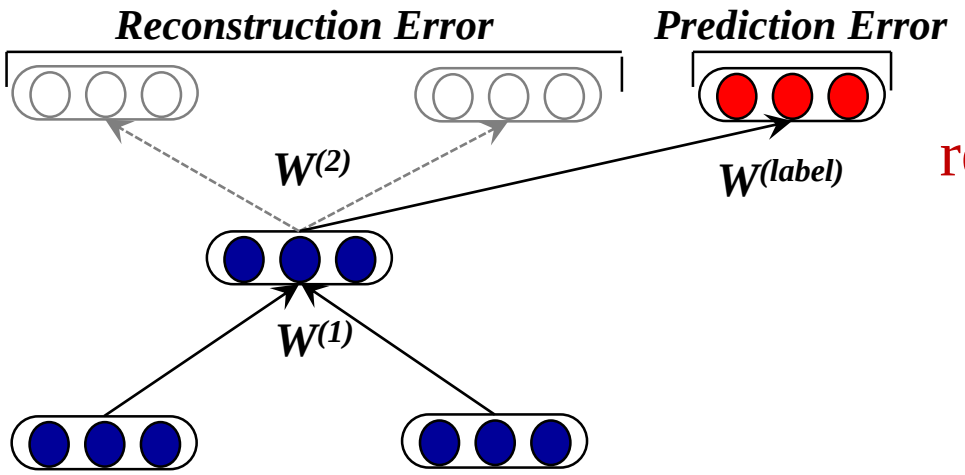
Semi-supervised RAE can **group** the phrases with the **same syntactic category, the same polarity and the same reordering pattern**

3. Bilingually-constrained Phrase Embedding

- **Problems of the Unsupervised and Semi-supervised Phrase Embedding**
  - Unsupervised phrase embedding
    - only learn some syntactic information of the phrase, but cannot learn the correct semantics
    - More like syntactic embedding
  - Semi-supervised phrase embedding
    - Group the phrases with the similar role (polarity or reordering pattern)
    - More like role embedding
  - How to learn semantic phrase embedding?

3. Bilingually-constrained Phrase Embedding

- **Extension to Semi-supervised Phrase Embedding**



If some gold semantic phrase representation are given as labels

We can learn how to embed each phrase semantically!

3. Bilingually-constrained Phrase Embedding

- Problem
  - We have no gold representation for any phrase
- What can we make full use of?
  - If phrases are represented semantically, two phrases sharing the same meaning should have the same phrase embedding
- What can we learn from the above fact?
  - If a model can always **learn the same representation** for any **phrase pairs which have the same meaning**, the representation **must encode the semantics** of the phrase, and **the model is our desire**

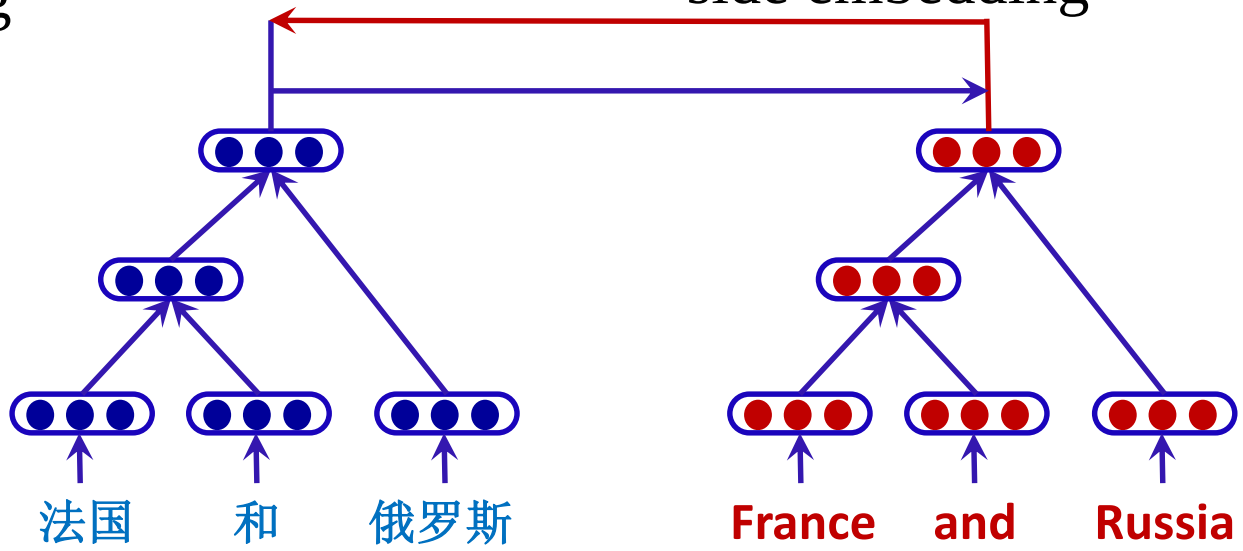
3. Bilingually-constrained Phrase Embedding

- **Bilingually-constrained Phrase Embedding**
  - What we need to learn the model?
    - The phrase pairs sharing the same meaning
  - Assumption
    - The phrase and its correct translation are in the same meaning, and the semantic representation between them should be the same (translation equivalents)

3. Bilingually-constrained Phrase Embedding

If source-side semantic phrase embedding is given, we can learn how to train the target-side embedding

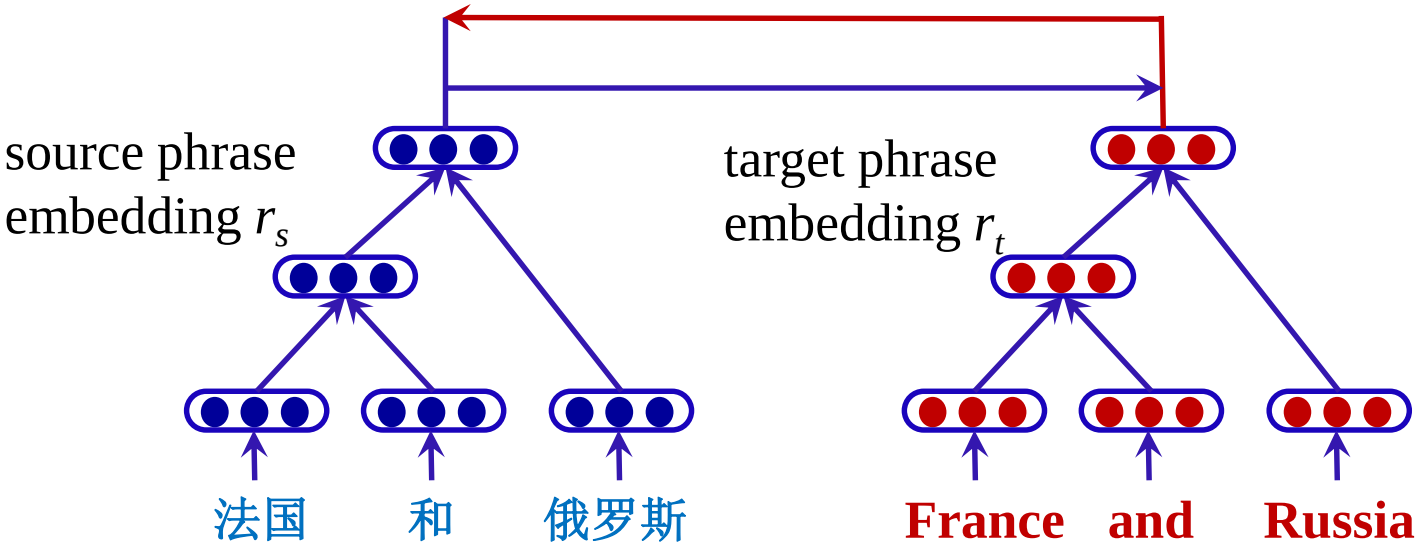
If target-side semantic phrase embedding is given, we can learn how to train the source-side embedding



- Basic Objective Function
  - Minimizing the semantic distance between the representations of the translation equivalents

3. Bilingually-constrained Phrase Embedding

- **Basic Objective Function**

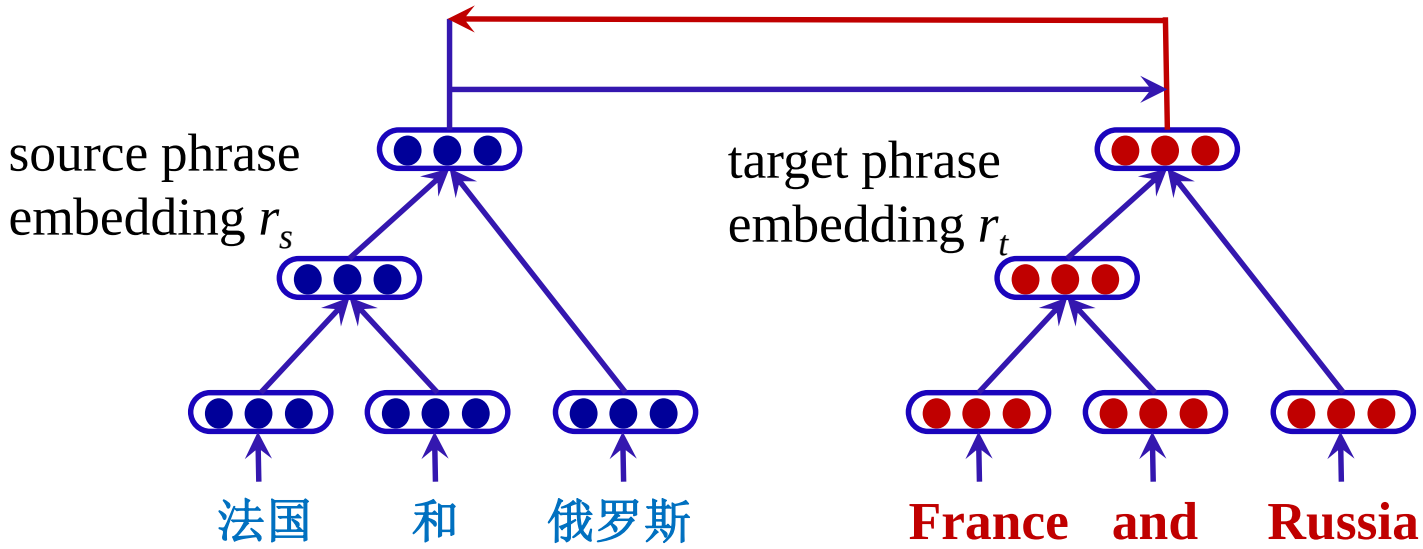


$$E(s,t;\theta) = \alpha E_{REC}(s,t;\theta) + (1-\alpha)E_{SEM}(s,t;\theta)$$

Reconstruction error

Semantic distance (error)

3. Bilingually-constrained Phrase Embedding

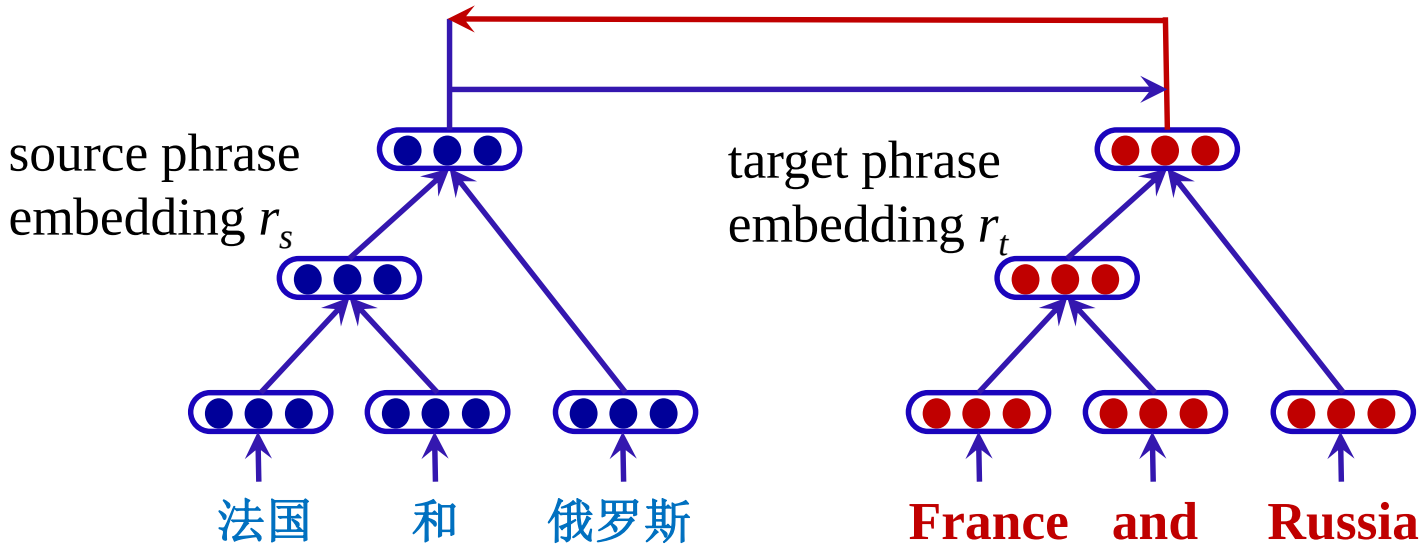


$$E_{REC}(s,t;\theta) = E_{REC}(s;\theta) + E_{REC}(t;\theta)$$

Source reconstruction error

Target reconstruction error

3. Bilingually-constrained Phrase Embedding

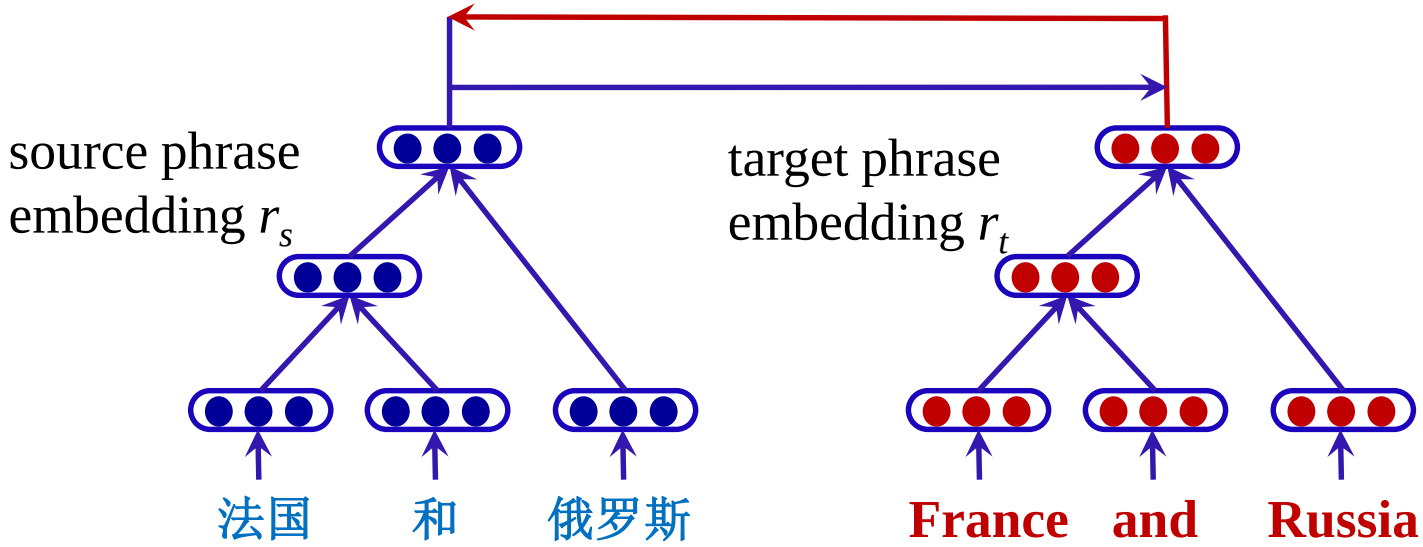


$$E_{SEM}(s,t;\theta) = E_{SEM}(s|t,\theta) + E_{SEM}(t|s,\theta)$$

The distance in the target embedding space

The distance in the source embedding space

3. Bilingually-constrained Phrase Embedding



$$E_{SEM}(s|t,\theta) = \frac{1}{2}\left\|p_t - f\left(W_s^l p_s + b_s^l\right)\right\|^2$$

$$E_{SEM}(t|s,\theta) = \frac{1}{2}\left\|p_s - f\left(W_t^l p_t + b_t^l\right)\right\|^2$$

3. Bilingually-constrained Phrase Embedding

$$E_{SEM}(s|t,\theta) = \frac{1}{2}\left\|p_t - f\left(W_s^l p_s + b_s^l\right)\right\|^2$$ ⬅ Translation Equivalents

Ideally, we require the distance between translation equivalents is much smaller than that between non-translation pairs

3. Bilingually-constrained Phrase Embedding

$$E_{SEM}(s|t,\theta) = \frac{1}{2}\left\|p_t - f\left(W_s^l p_s + b_s^l\right)\right\|^2$$ ⇐ Translation Equivalents

⇓ Max-Semantic-Margin

non-translation pair ⇑

$$E^*_{SEM}(s|t,\theta) = \max\{0, E_{SEM}(s|t,\theta) - E_{SEM}(s|t',\theta) + 1\}$$

3. Bilingually-constrained Phrase Embedding

- **Parameter Training**

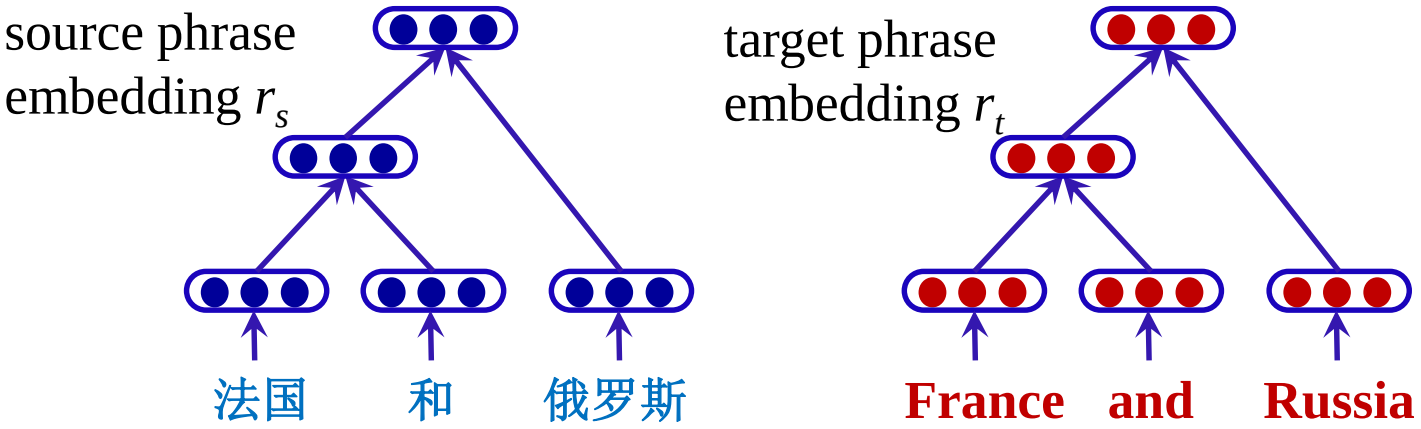
$$E(s,t;\theta) = \alpha E_{REC}(s,t;\theta) + (1-\alpha)E_{SEM}(s,t;\theta)$$
$$= \alpha(E_{REC}(s;\theta) + E_{REC}(t;\theta)\ )$$
$$+ (1-\alpha)\left(E^*_{SEm}(s|t,\theta) + E^*_{SEM}(t|s,\theta)\right)$$
$$= \alpha E_{REC}(s;\theta) + (1-\alpha)E^*_{SEM}(s|t,\theta)$$
$$+ \alpha E_{REC}(t;\theta) + (1-\alpha)E^*_{SEM}(t|s,\theta)$$

source-side parameters can be tuned as long as the representation of the target phrase is given

target-side parameters can be tuned as long as the representation of the source phrase is given

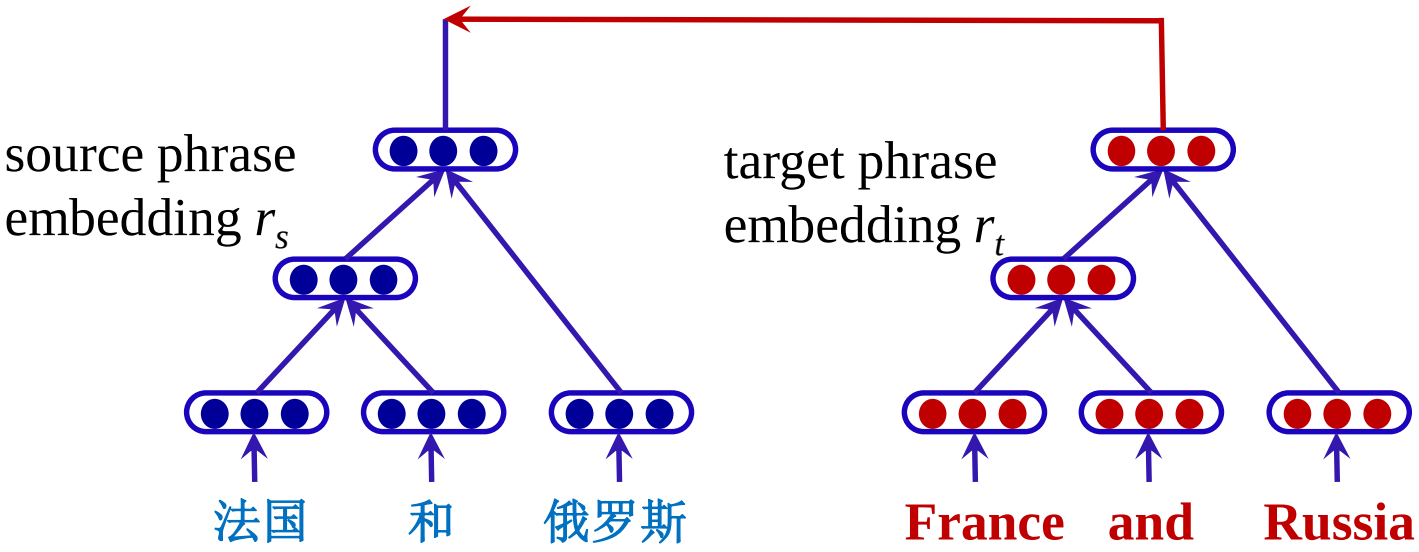
3. Bilingually-constrained Phrase Embedding

- **Co-training style Training Algorithm**



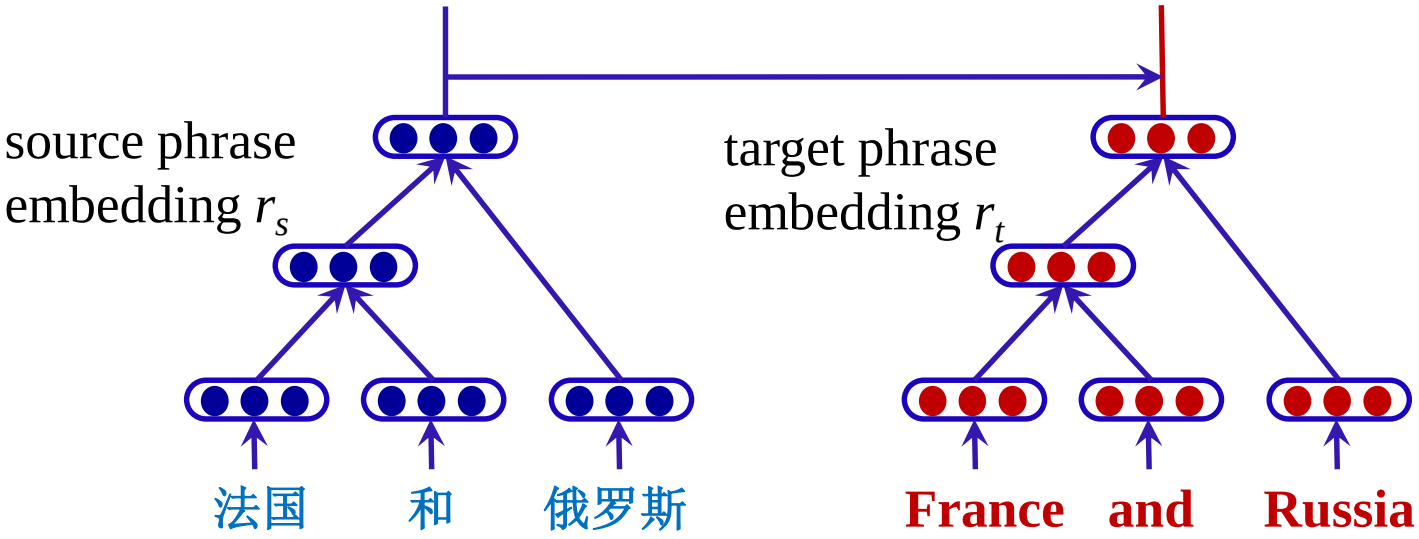
<u>Step 1</u>, Pre-training: learn respectively the source and target phrase embedding with standard unsupervised RAEs

3. Bilingually-constrained Phrase Embedding



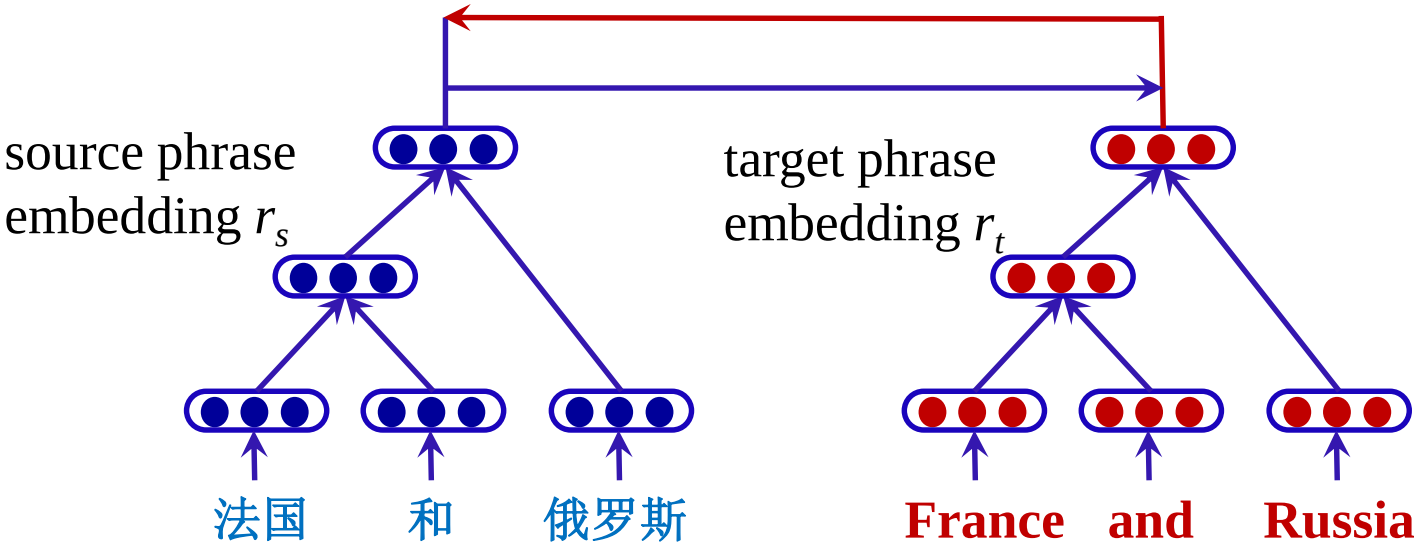
Step 2, **Fine-tuning:** a) regard target phrase embedding *as* the gold semantic representation of source phrase, and then refine the parameters for source phrase embedding process;

3. Bilingually-constrained Phrase Embedding



<u>Step 2</u>, Fine-tuning: b) regard source phrase embedding *as* the gold semantic representation of target phrase, and then refine the parameters for target phrase embedding process

3. Bilingually-constrained Phrase Embedding



Step 3, **Termination Check:** If overall error reaches a minima or the iterations reach the pre-defined number, we terminate, otherwise, we update the source and target phrase representations and go to Step 2

3. Bilingually-constrained Phrase Embedding

- Some good examples

	military force
Similar ones:	military power armed forces
	do not agree
Similar ones:	do not favor not to approve
	each people in this nation
Similar ones:	all the people in the country people all over the country

3. Bilingually-constrained Phrase Embedding

- **Experiments**
  - **Usage of Phrase Embedding in SMT**
    - For each phrase pair in phrase table, after obtaining source and target phrase embedding p_s and p_t, map p_s into target space p'_s and semantic similarity $Sem(p'_s, p_t)$; similarly, we can get $Sem(p'_t, p_s)$,
    - As another two translation features, integrate in phrase-based decoding
    - Use the $Sem(p'_s, p_t)$ and $Sem(p'_t, p_s)$ to prune phrase table

3. Bilingually-constrained Phrase Embedding

- **Experimental Setup**
  - Decoder: MEBTG
  - Training: 0.96M bitext + 1.1M entity pairs, English Gigaword Xinhua News
  - Tuning set: NIST03
  - Test set: NIST04, NIST05, NIST06, NIST08 (news part in NIST06-08)

3. Bilingually-constrained Phrase Embedding

- **As extra two features**

System	NIST03	NIST04	NIST05	NIST06	NIST08	ALL
MEBTG	35.81	36.91	34.69	33.83	27.17	34.82
+2feats 50-dim	36.43 (0.62↑)	37.64 (**0.73**↑)	35.35 (0.66↑)	35.53 (**1.70**↑)	28.59 (**1.42**↑)	35.84 (1.02↑)
+2feats 100-dim	36.45 (**0.64**↑)	37.44 (0.53↑)	35.58 (0.89↑)	35.42 (1.59↑)	28.57 (1.40↑)	36.03 (**1.21**↑)
+2feats 200-dim	36.34 (0.53↑)	37.35 (0.44↑)	35.78 (**1.09**↑)	34.87 (1.04↑)	27.84 (0.67↑)	35.62 (0.80↑)

3. Bilingually-constrained Phrase Embedding

- **Phrase table pruning**

System	Phrase-Table	NIST03	NIST04	NIST05	NIST06	NIST08	ALL
MEBTG	100%	35.81	36.91	34.69	33.83	27.17	34.82
0.4	52%	35.94	36.96	35.00	34.71	27.77	**35.16**
0.5	44%	35.67	36.59	34.86	33.93	27.25	**34.89**
0.6	35%	35.86	36.71	34.93	34.63	27.34	**35.05**
0.7	**28%**	35.55	36.62	34.57	33.97	27.10	**34.76**
0.8	20%	35.06	36.01	34.13	33.04	26.66	34.04

3. Bilingually-constrained Phrase Embedding

Summary on phrase embedding

- Bilingually-constrained Phrase Embedding
  - Can learn how to semantically embed both source and target phrases
  - Can learn how to transform the semantic embedding space in one language to the other

- The model is proven to be effective in phrase table pruning and decoding with phrasal semantic similarity

3. Bilingually-constrained Phrase Embedding

For more details about this work, please refer to:

J. Zhang, S. Liu, M. Li, M. Zhou and C. Zong. Bilingually-constrained Phrase Embeddings for Machine Translation. *Proc. of ACL'2014*, June 23 - 25, 2014, Baltimore, USA. Pages 111-121

Outline

1. Introduction
2. Diverse Features for SMT Model Pruning
3. Bilingually-constrained Phrase Embedding
4. Conclusion

Conclusion

- **Speech and translation quality**
  - Pruning phrase table or translation rule for PBTM and HPBTM

    - Whether the source syntactic information has the same effect in English-to-Chinese translation?

    - What type of phrase/ rule should be pruned?

  - Development of an approach to phrase embedding
- **How to combine the two work?**

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谢谢！
Thanks!