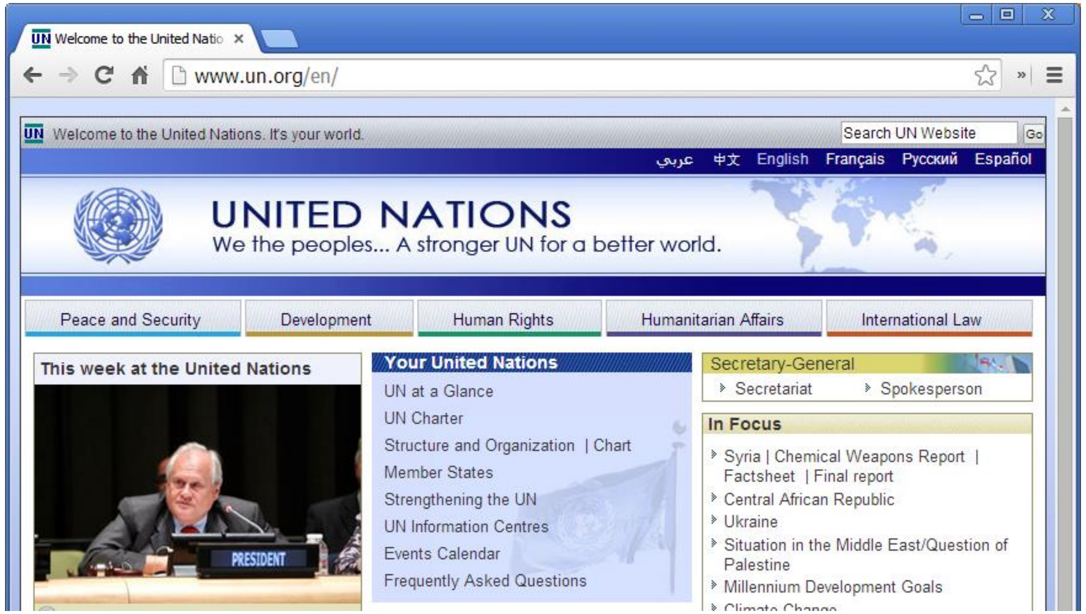
Learning to translate with neural networks

Michael Auli

Microsoft Research

What happened in MT over the past 10 years?



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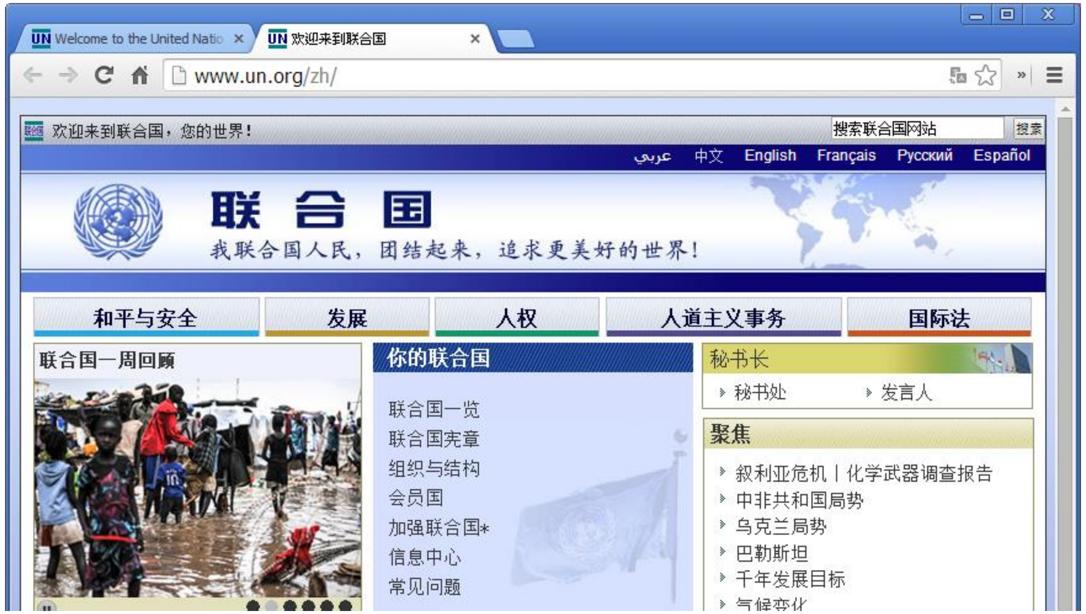

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- 中非共和国局势
- 乌克兰局势
- 巴勒斯坦
- 千年发展目标
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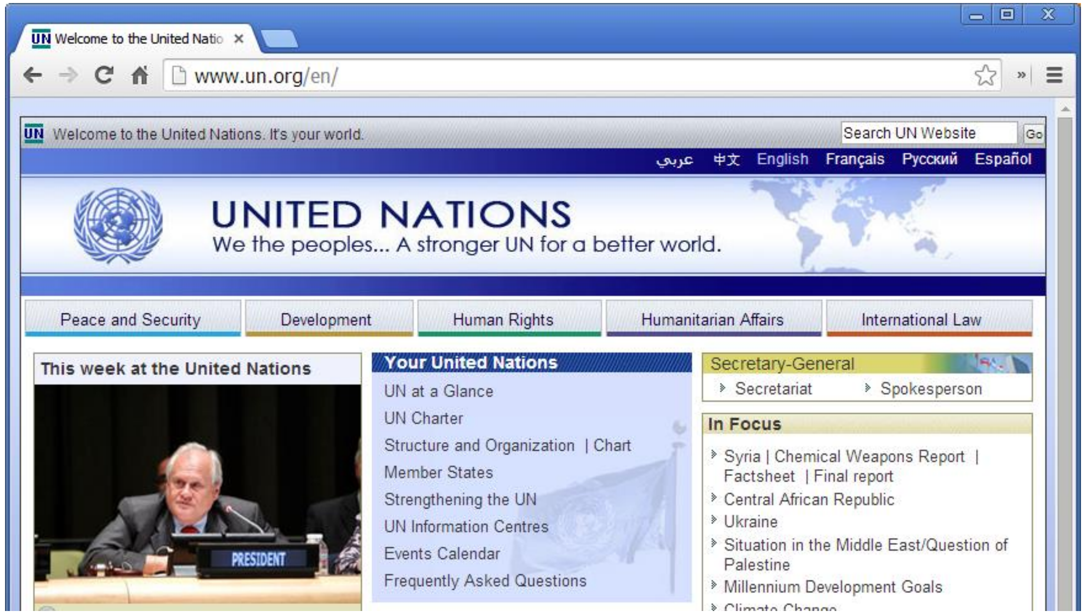

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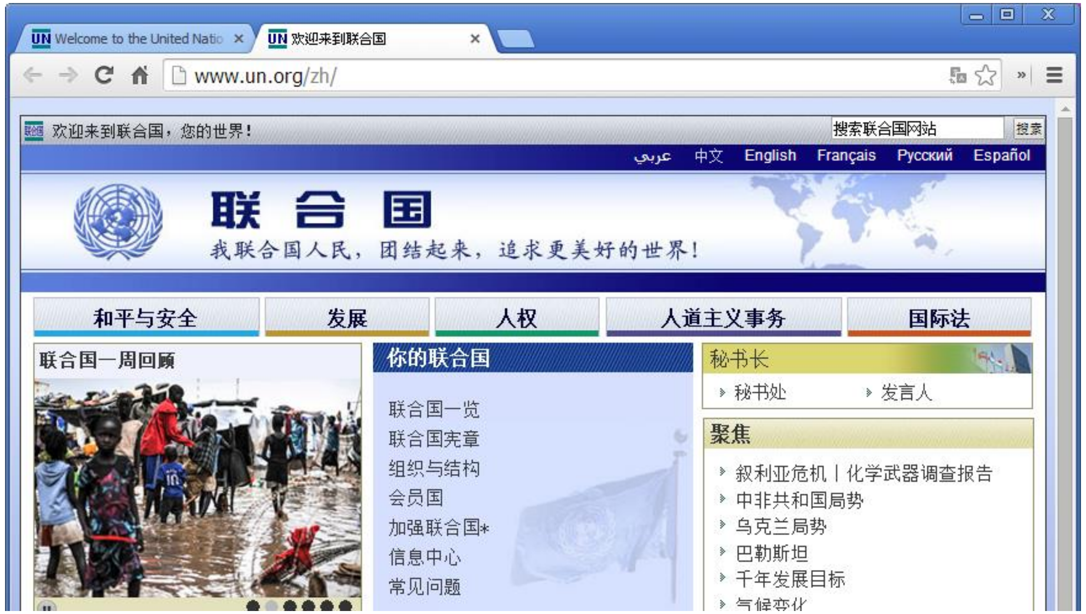

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“Learning **simple models** from large bi-texts is a solved problem”

(Lopez & Post, 2013)

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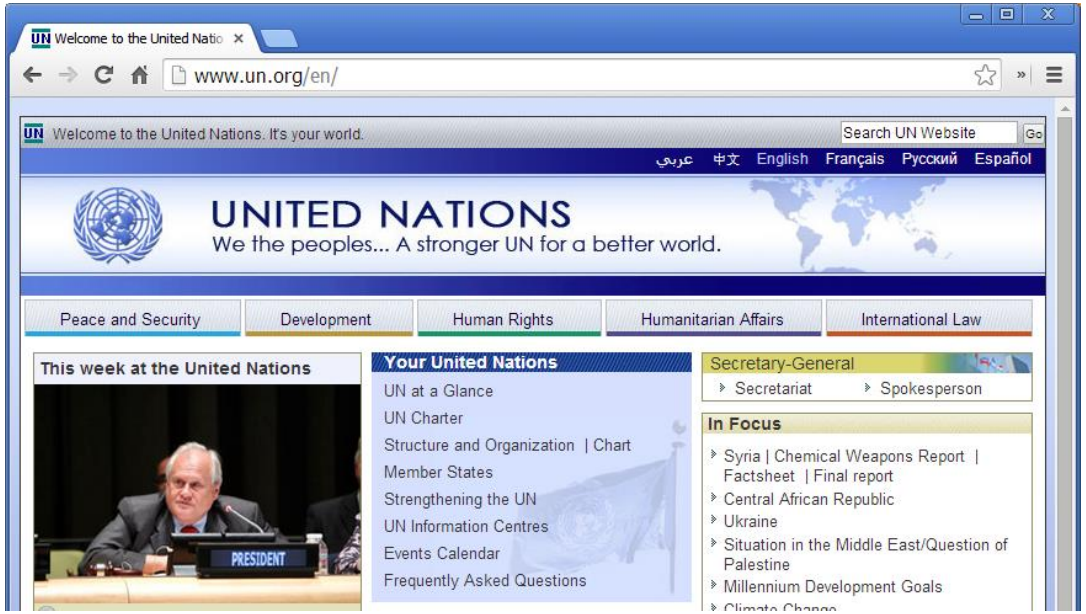

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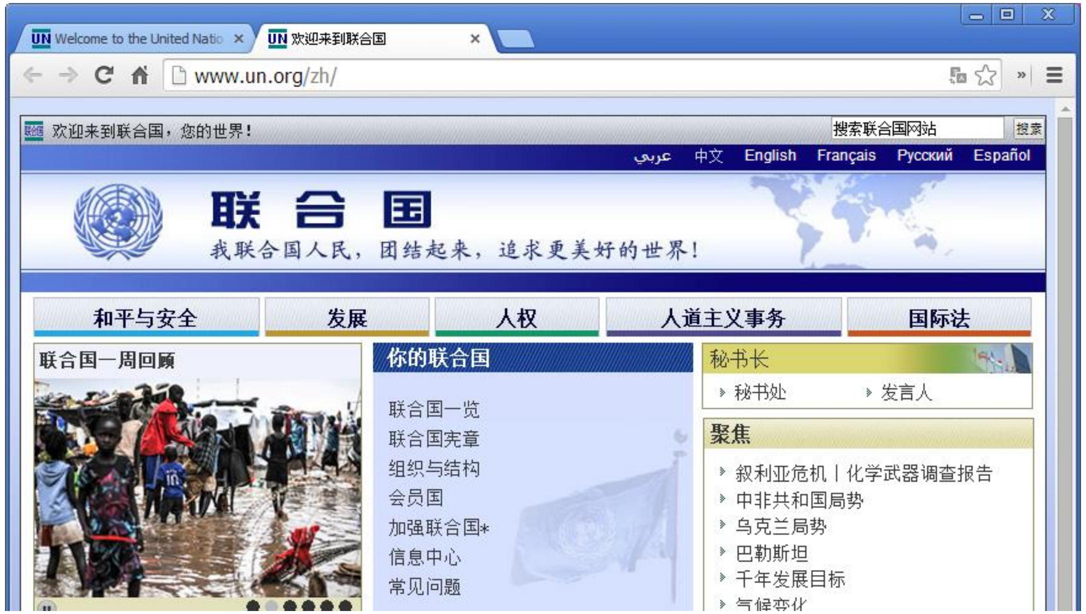

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Phrase-based Translation

Koehn et al. (2003)

本 地区 的 发展 和 进步 。

development and progress of the region .

Phrase-based Translation

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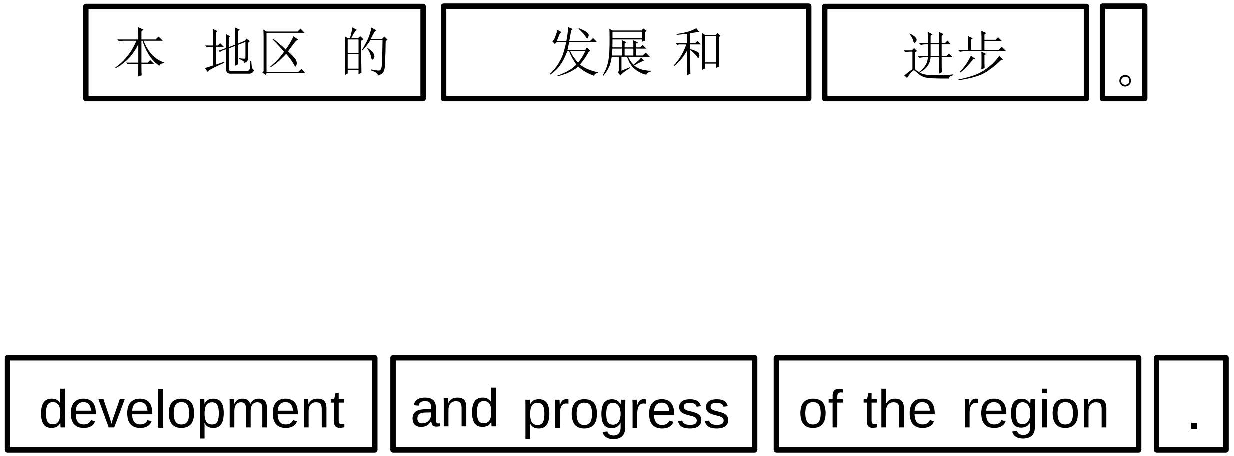

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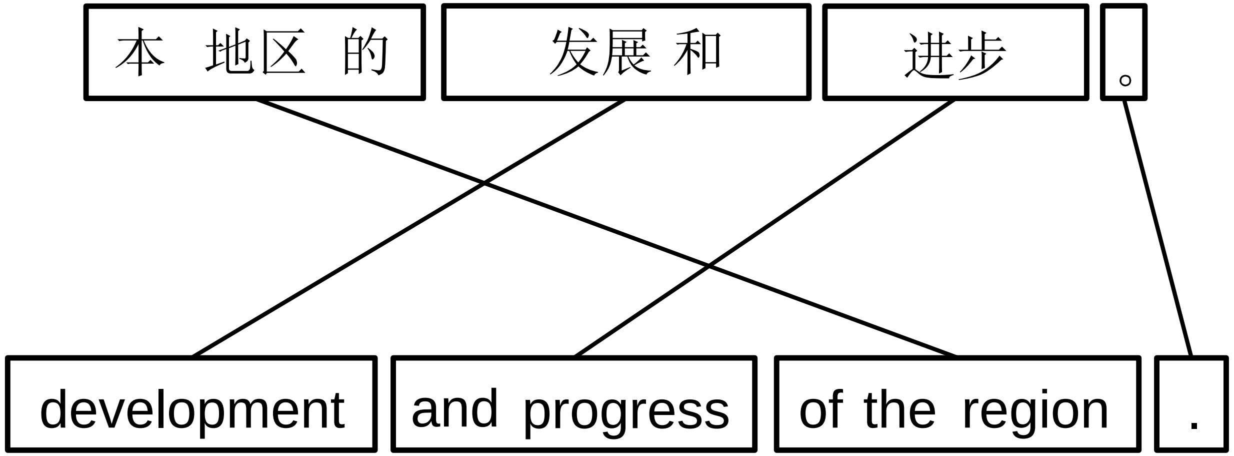

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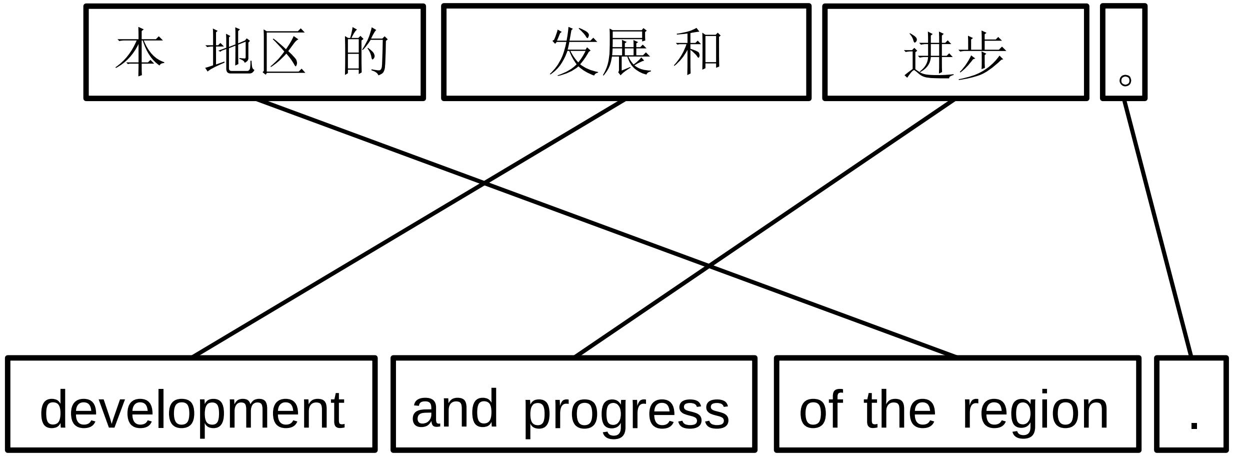

本 地区 的 → of the region

发展 → development

和 进步 → and progress

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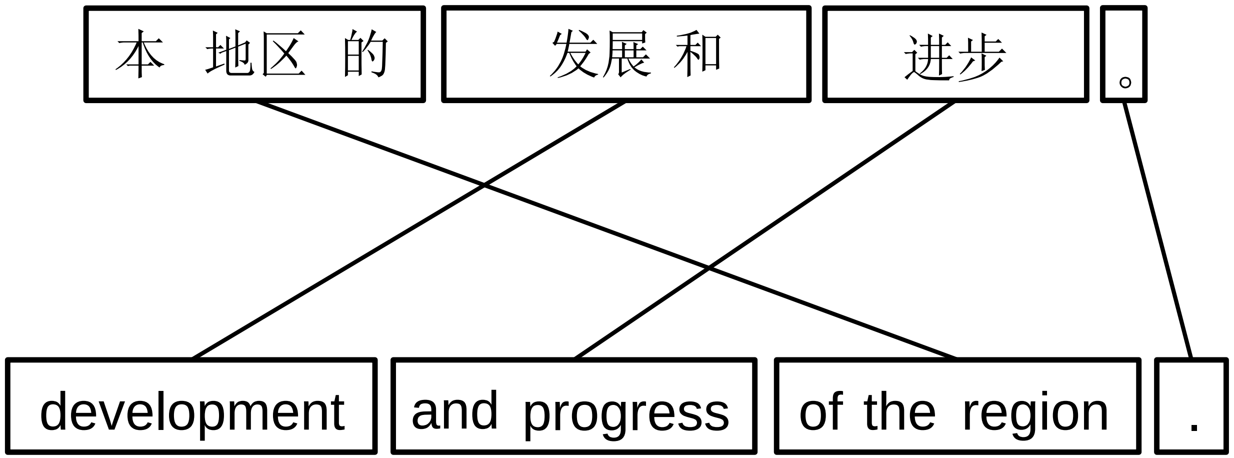
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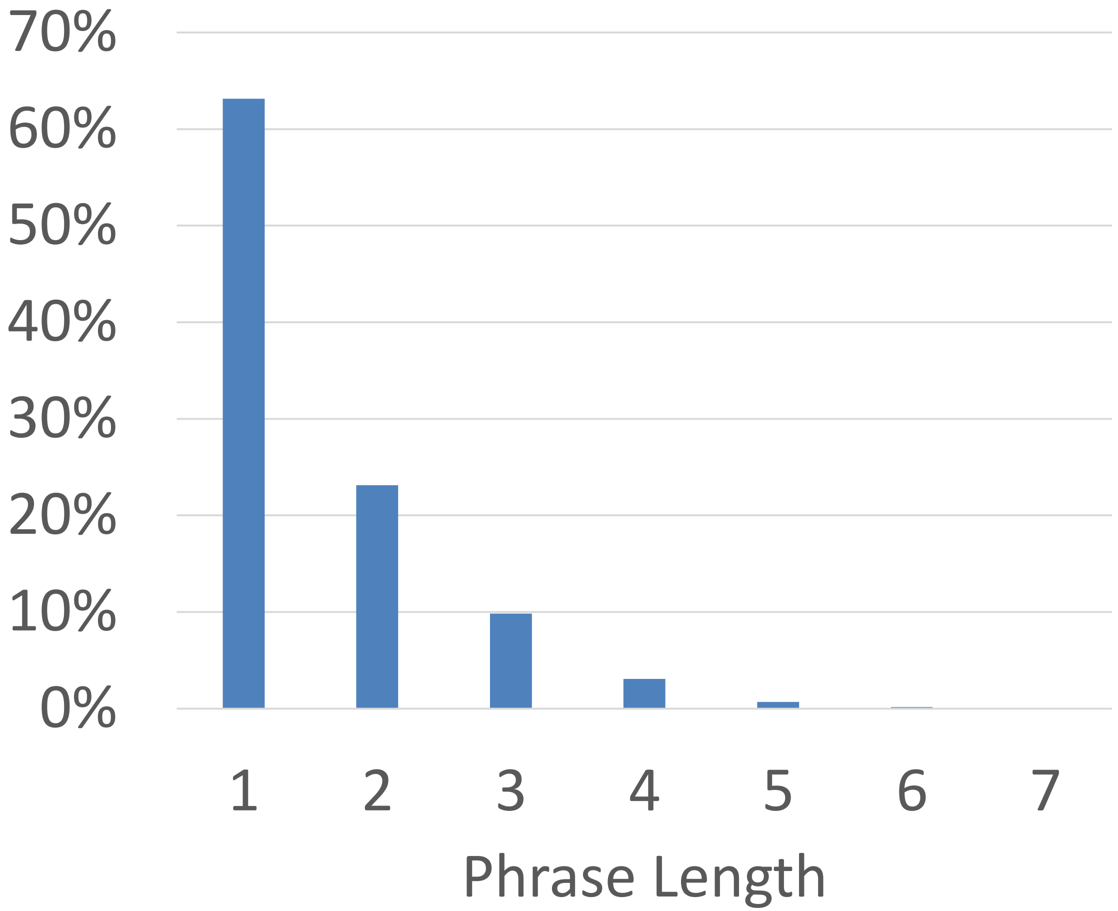

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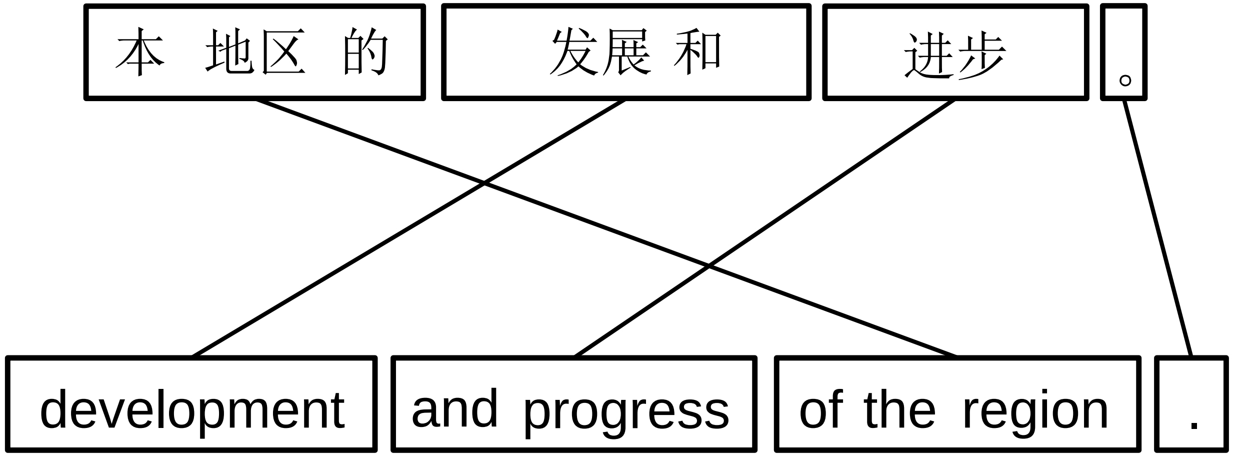

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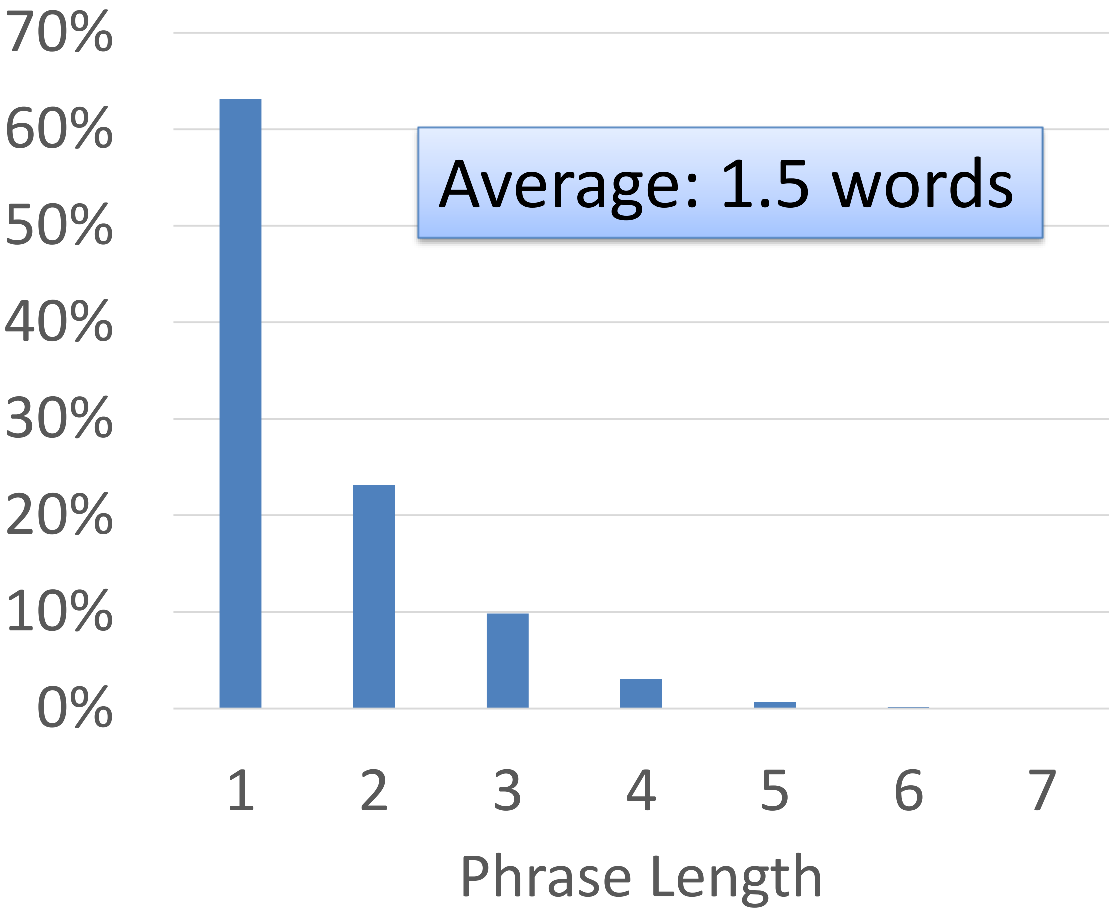

Average: 1.5 words

n-gram Language Modeling

Kneser & Ney (1996)

p(progress in the region) =

n-gram Language Modeling

Kneser & Ney (1996)

p(progress in the region) =

Train data:

…
development and progress of the region
…

n-gram Language Modeling

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p(progress in the region) =
p(progress) p(in)
p(the) p(region|the)

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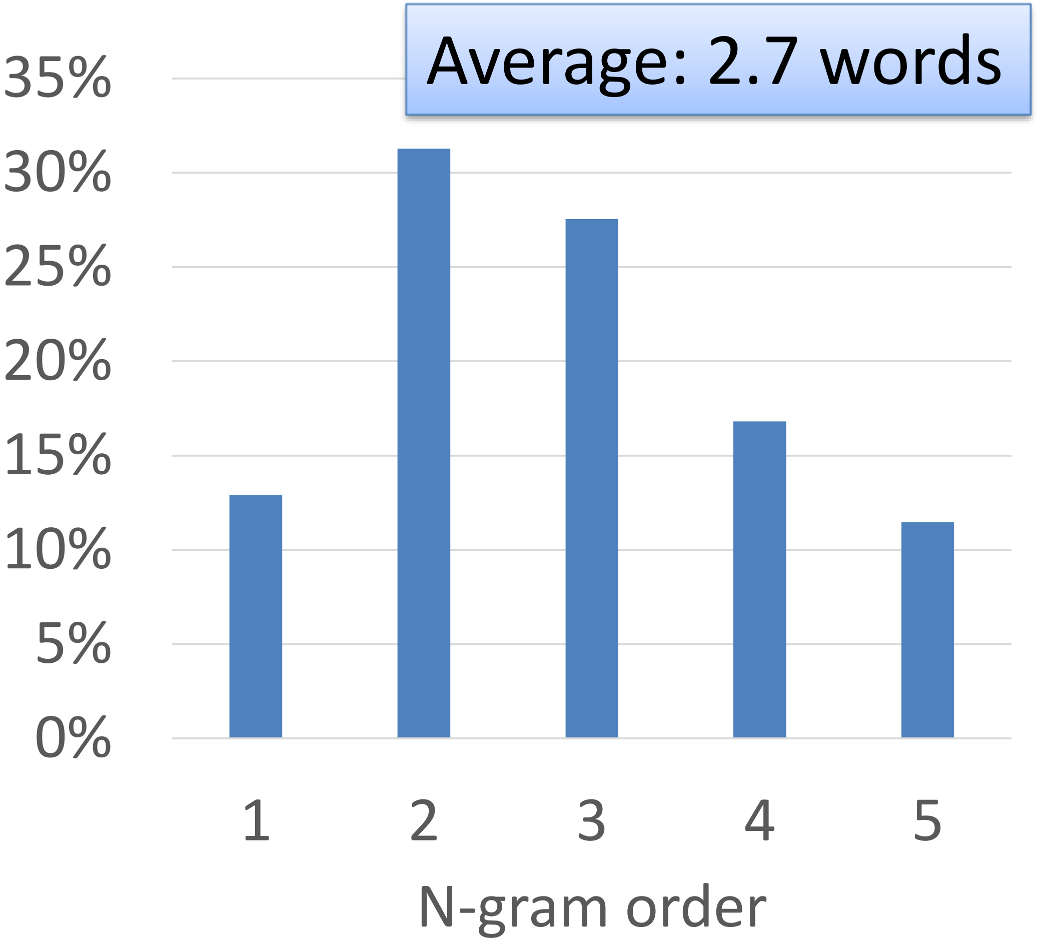

Does not include out-of-vocabulary tokens

How can we improve on this?

- Or: how to capture relationships beyond 1.5 - 2.7 words
- Neural networks: From discrete to distributional representations
- Recurrent nets: From fixed length contexts to unbounded histories

Overview

- Recurrent neural network joint models (Auli et al., EMNLP 2013)
  Combined language and translation modeling

- Minimum translation modeling with recurrent nets (Hu et al., EACL 2014)
  Sequence models over bilingual units

- Training recurrent nets (Auli & Gao, ACL 2014)
  Expected BLEU training for neural network translation models

- Large-scale discriminative sparse ordering models (Auli et al., in submission)
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Feed-forward Network

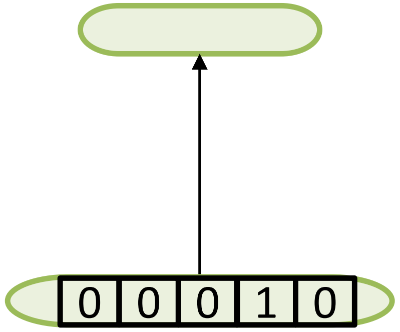
and

Feed-forward Network

0	0	0	1	0

and

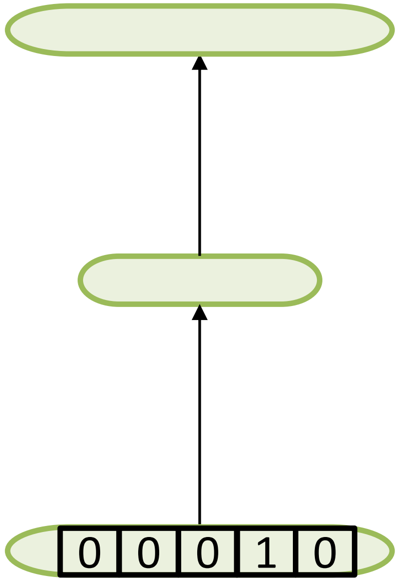
Feed-forward Network



0	0	0	1	0

and

Feed-forward Network



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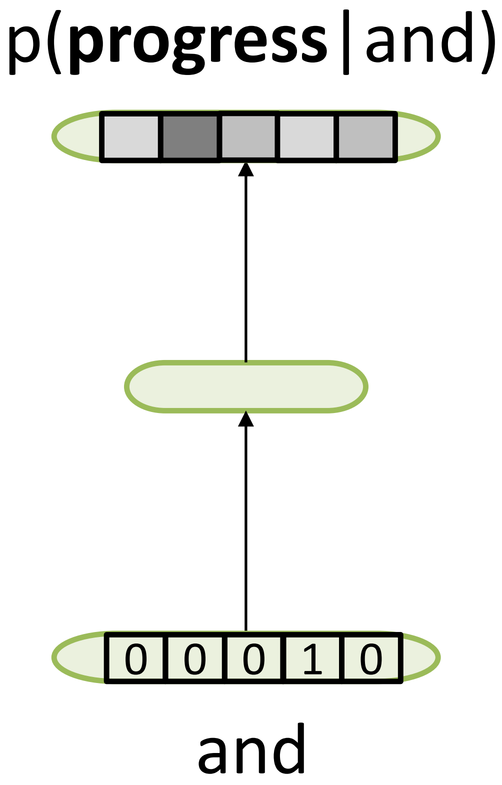
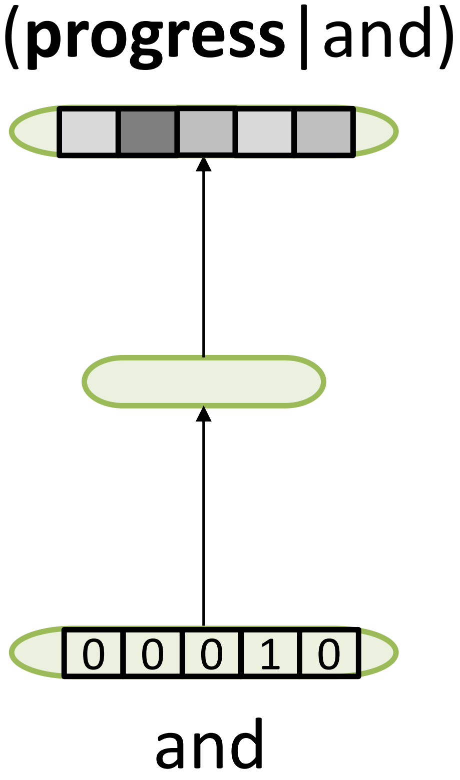


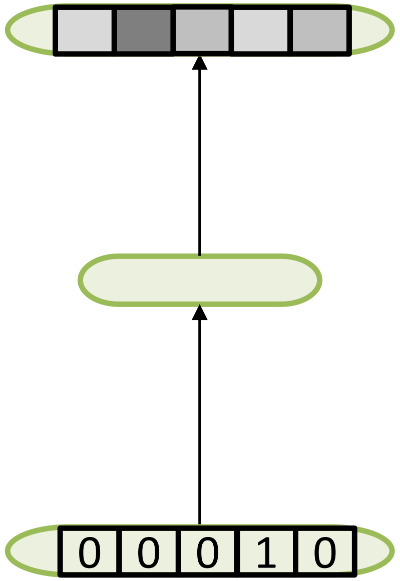
Feed-forward Network



Still based on limited context!

Recurrent Network

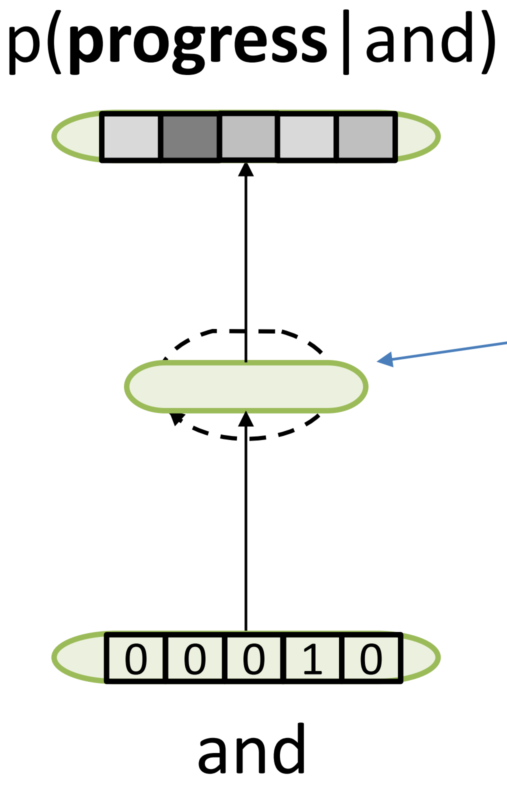
p(**progress**|and)



0	0	0	1	0

and

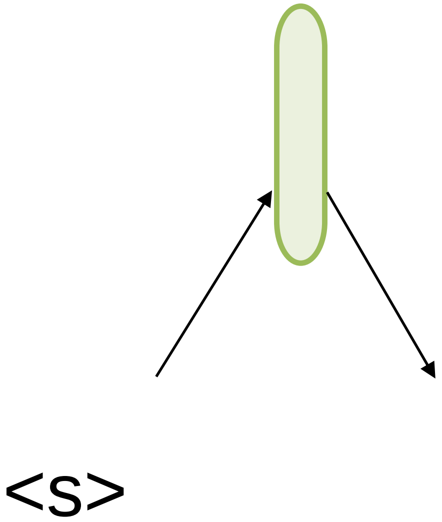
Recurrent Network



Dependence on
previous time steps

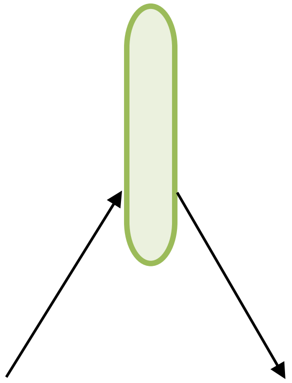
Recurrent Network

Recurrent Network



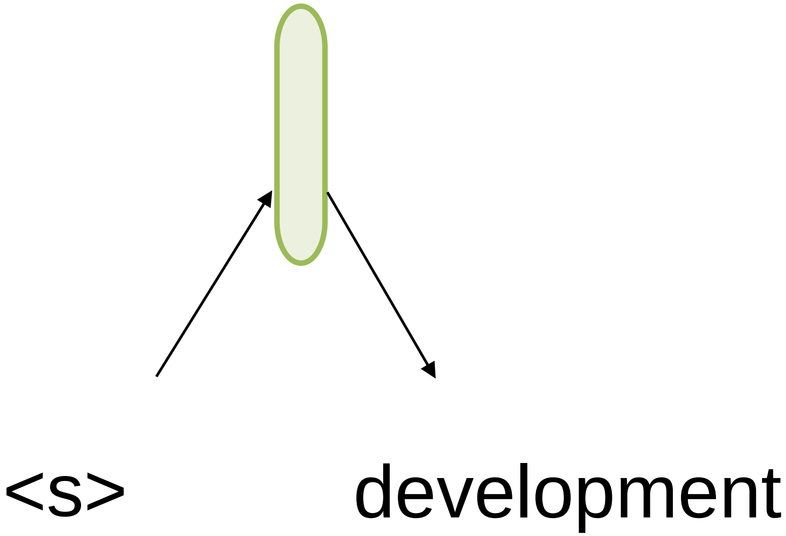
<s>

Recurrent Network



<s> p(development|<s>)

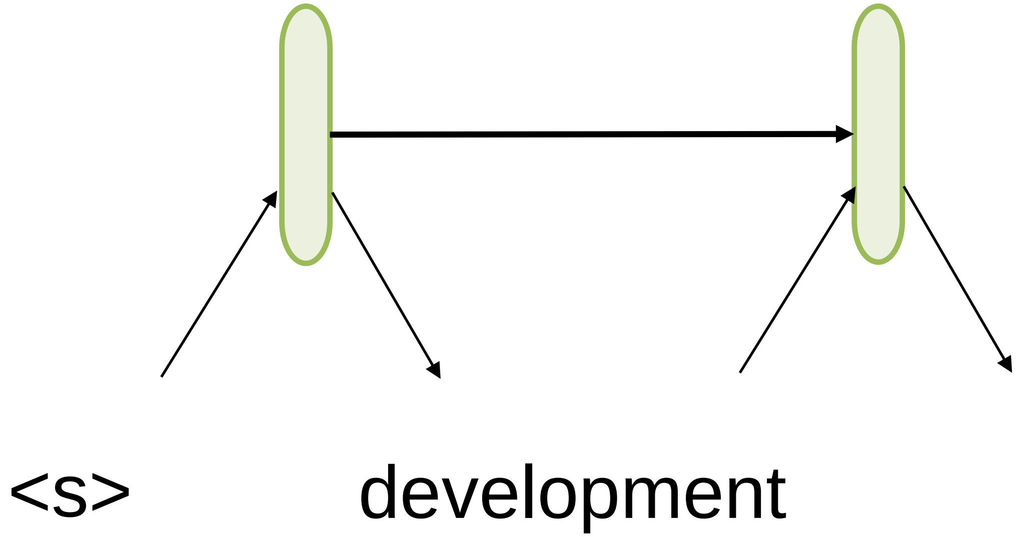
Recurrent Network



<s>

development

Recurrent Network



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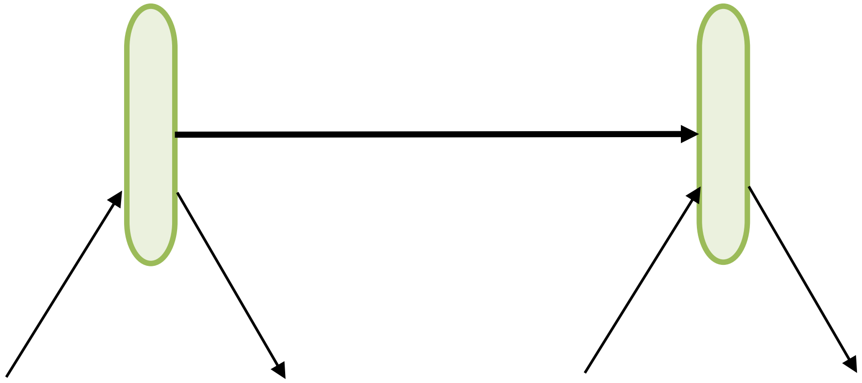
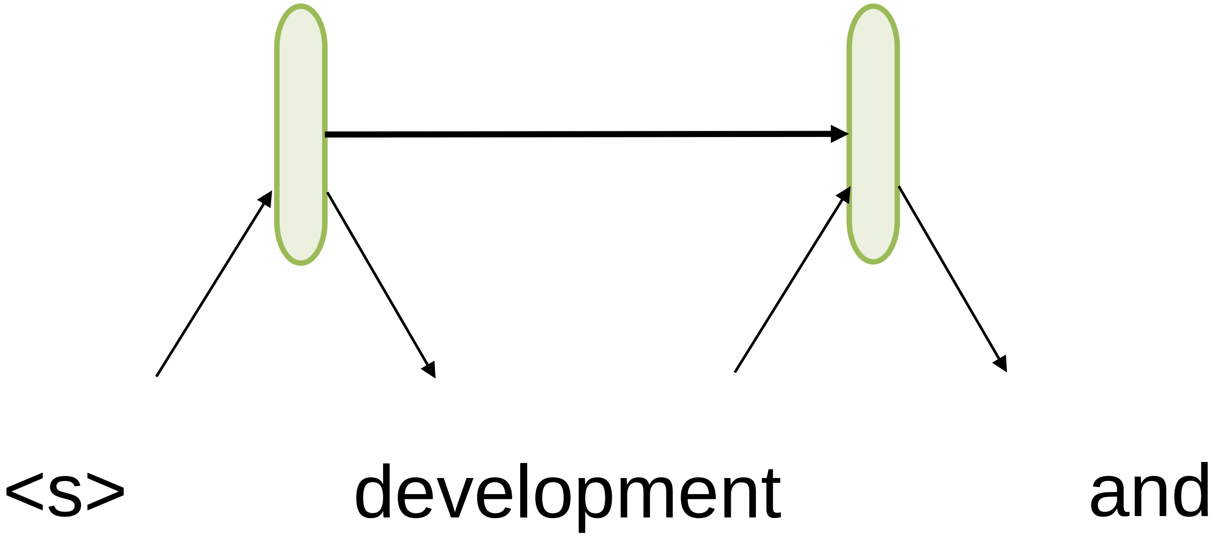


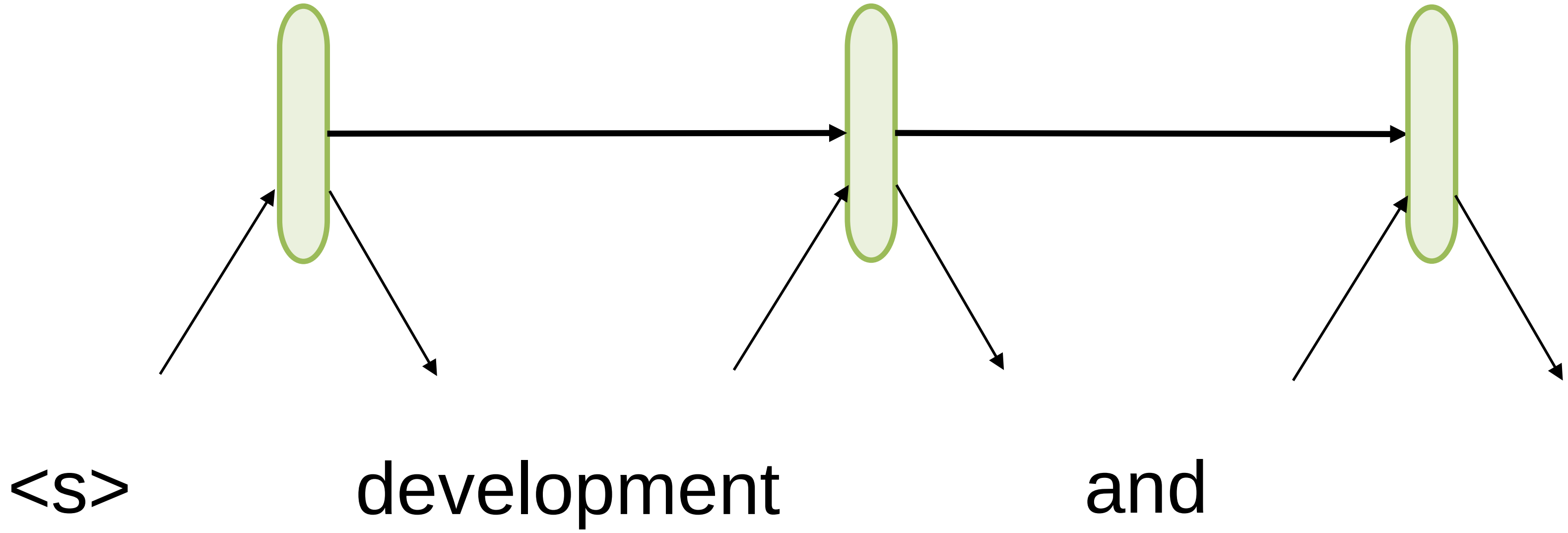
<s> development p(and|development, <s>)

Recurrent Network



<s> development and

Recurrent Network



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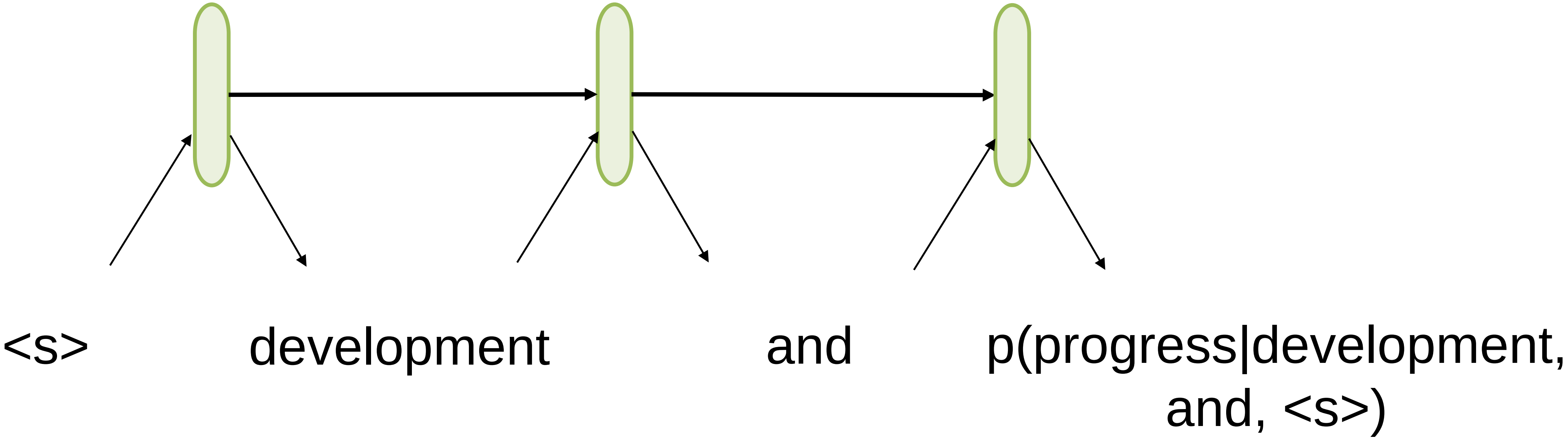

<s>

development

and

p(progress|development,
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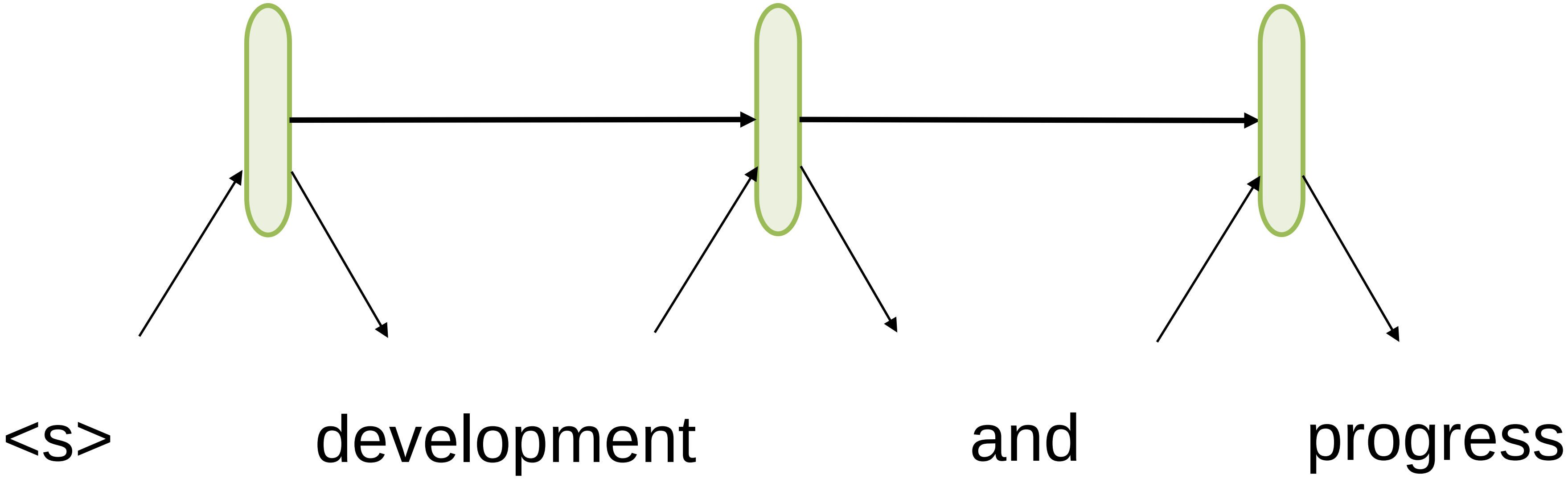
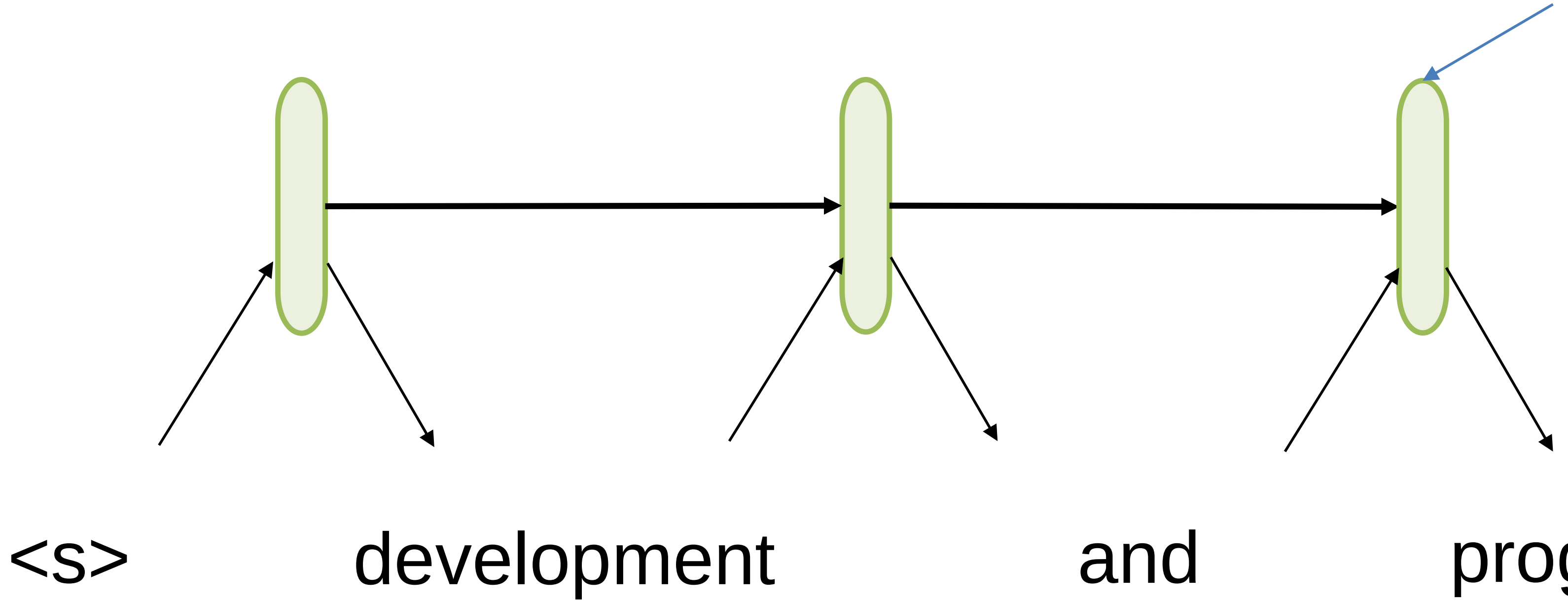


<s> development and progress

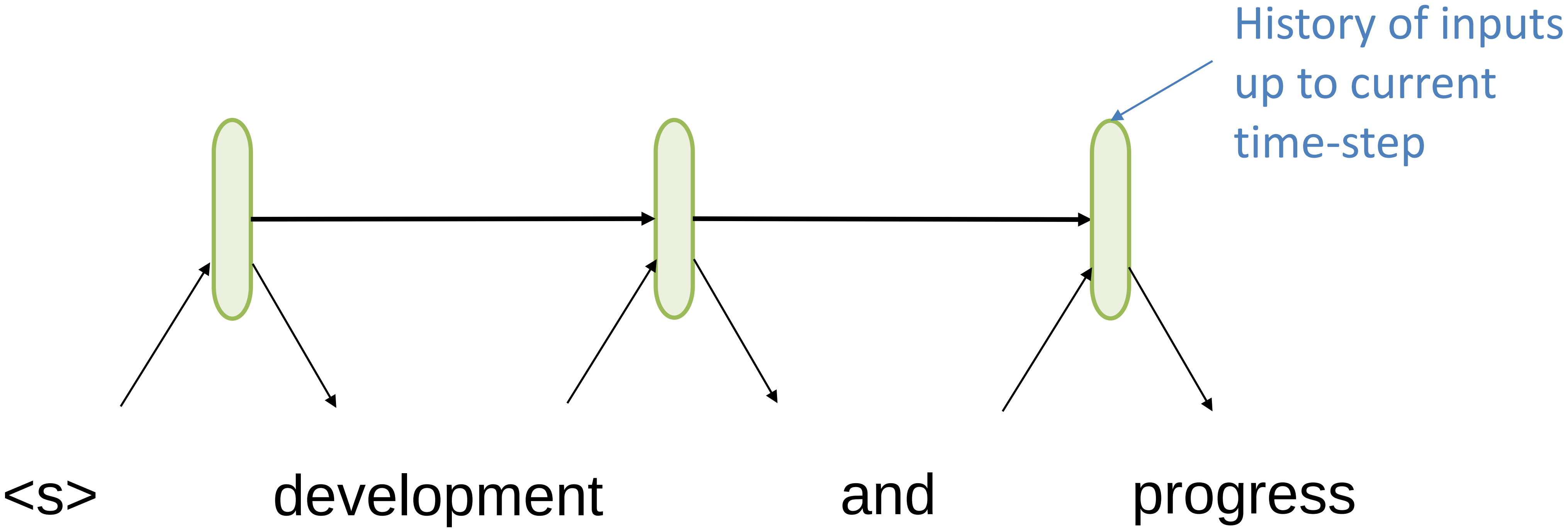
Recurrent Network



History of inputs up to current time-step

<s> development and progress

Recurrent Network



History of inputs up to current time-step

<s> development and progress

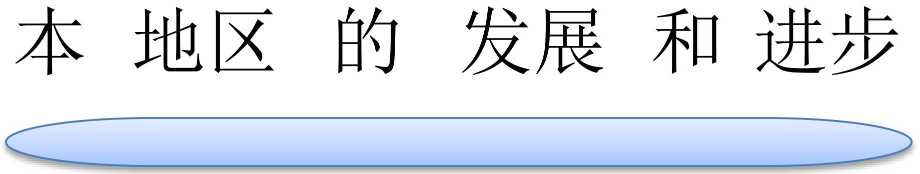
State of the art in language modeling (Mikolov 2011)

More accurate than feed-forward nets (Sundermeyer 2013)

Recurrent Network Joint Model

本 地区 的 发展 和 进步

Recurrent Network Joint Model



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Entire source sentence representation

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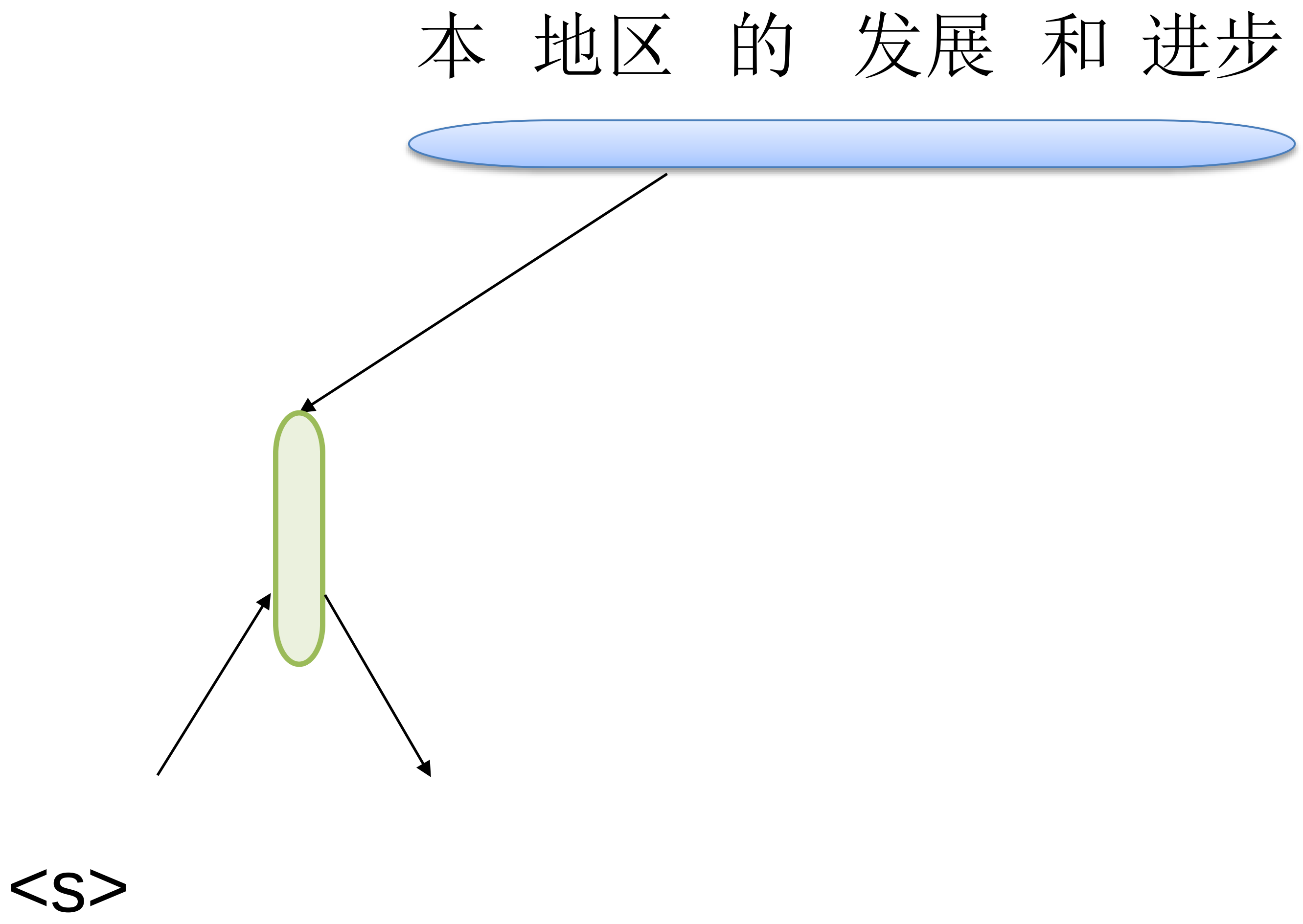

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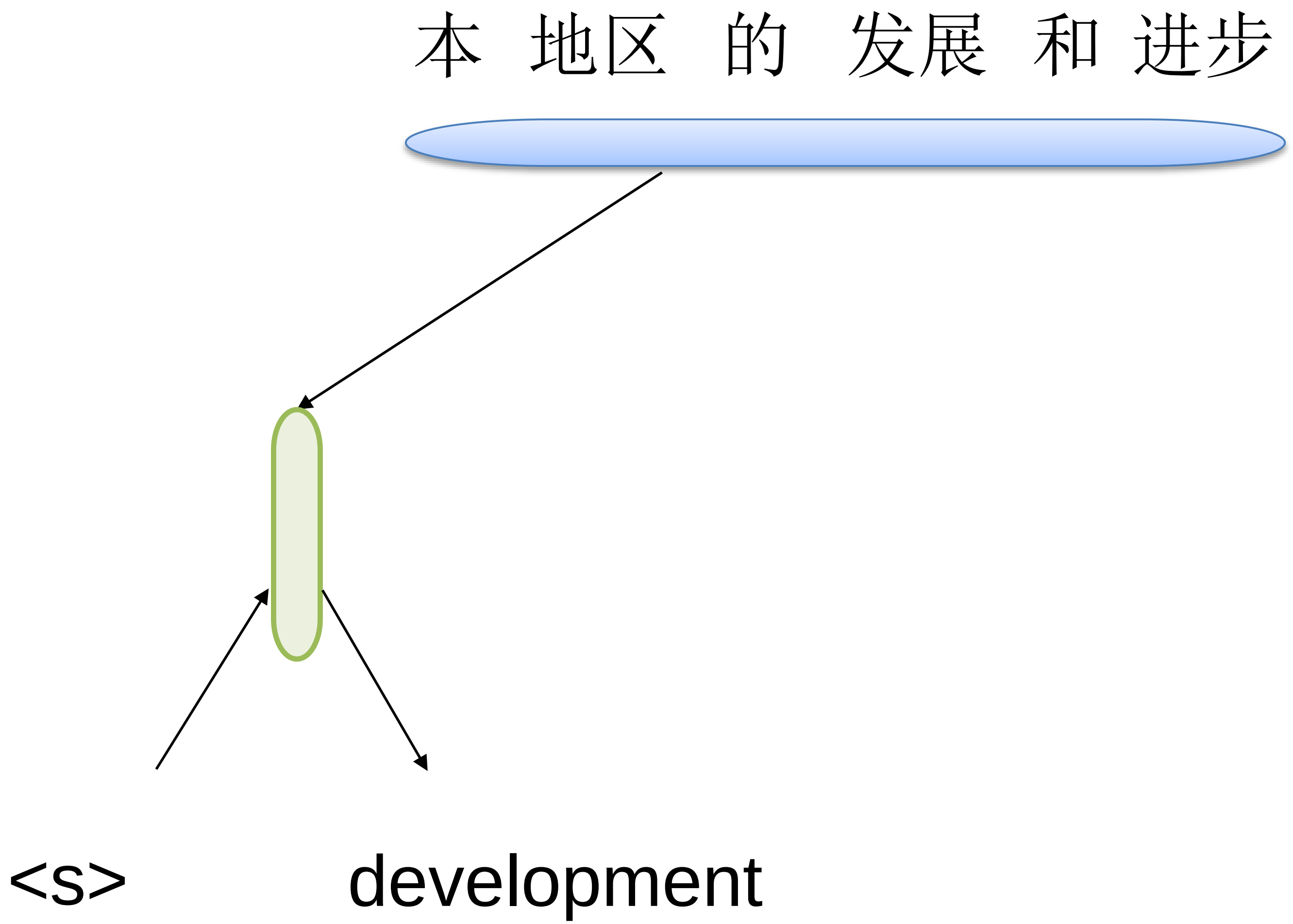

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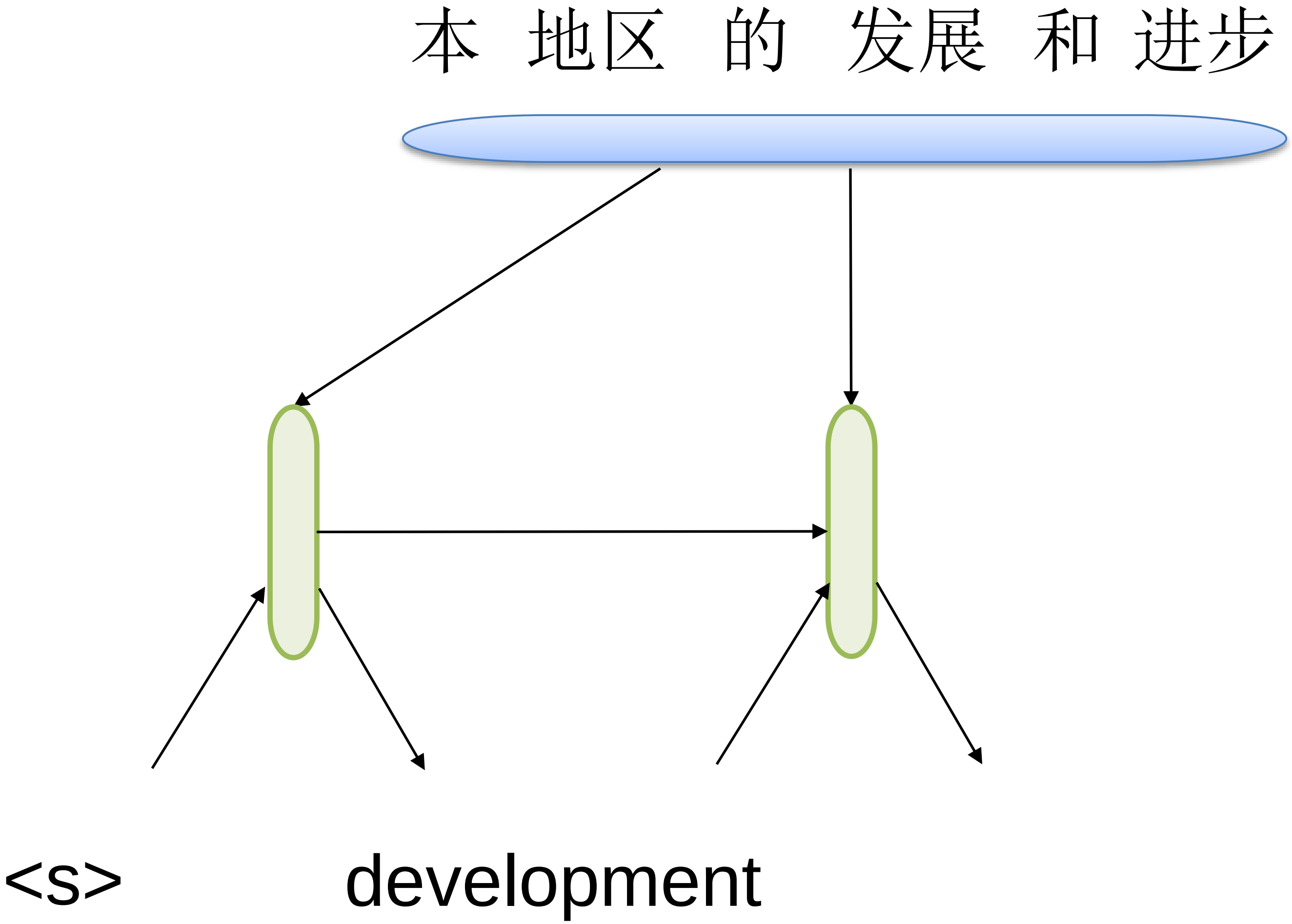

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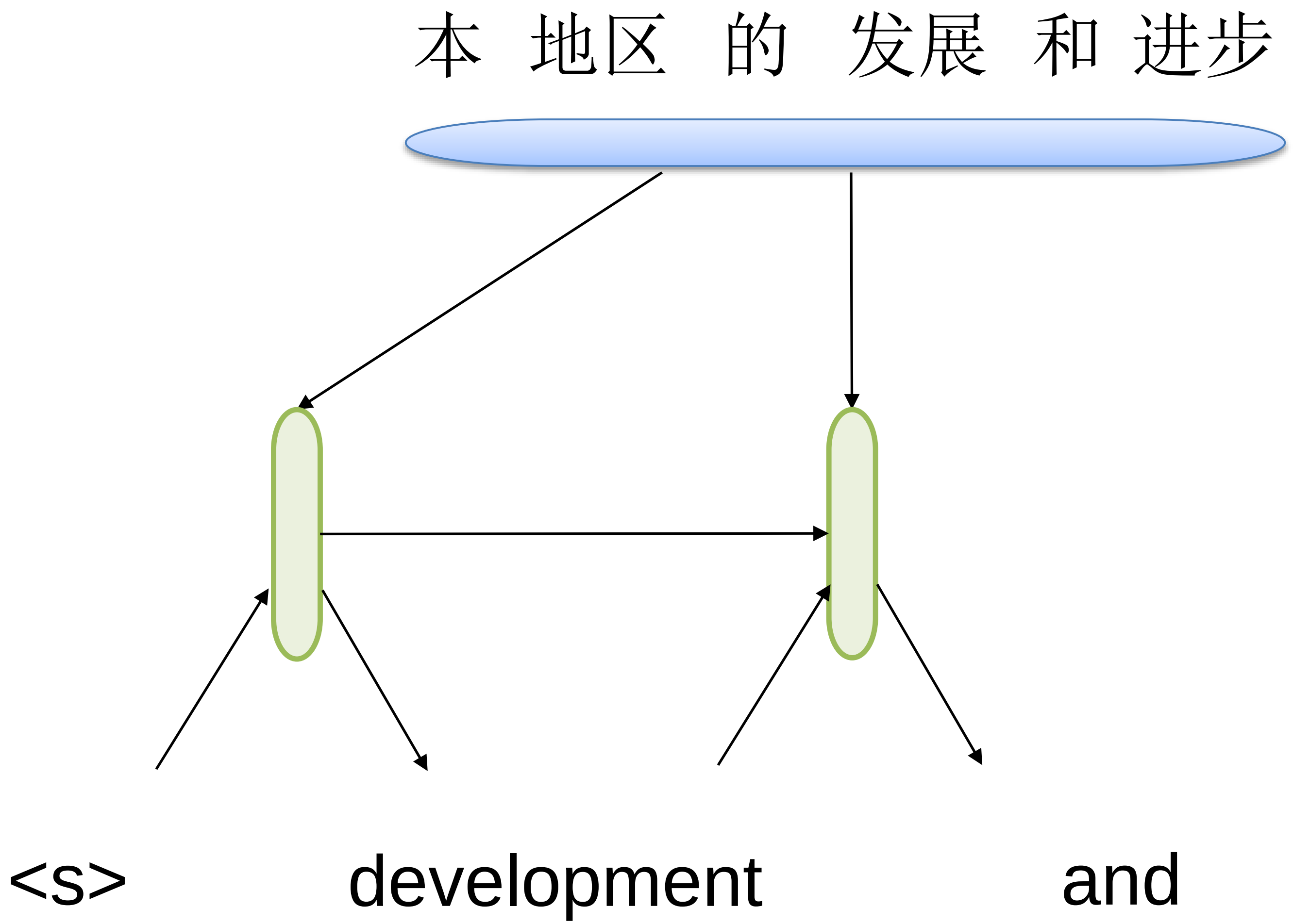

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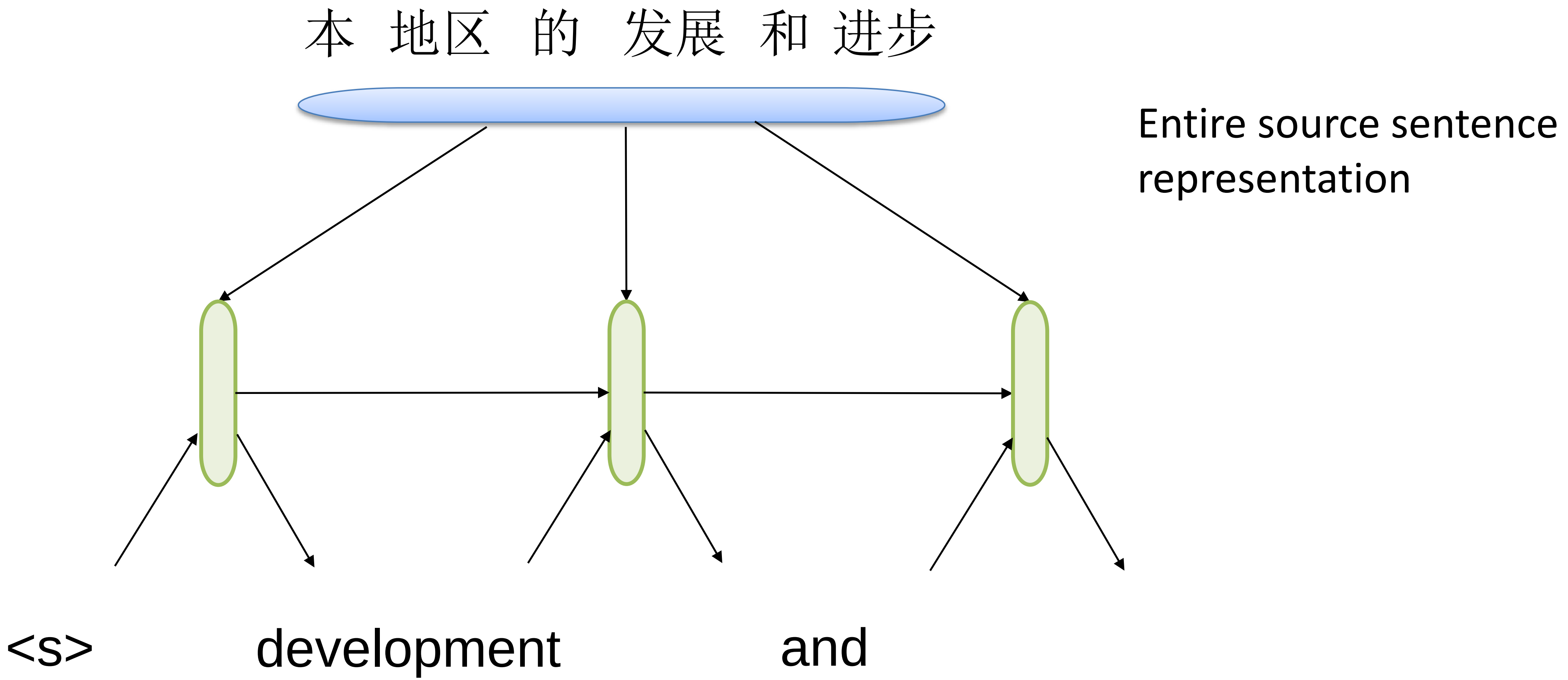

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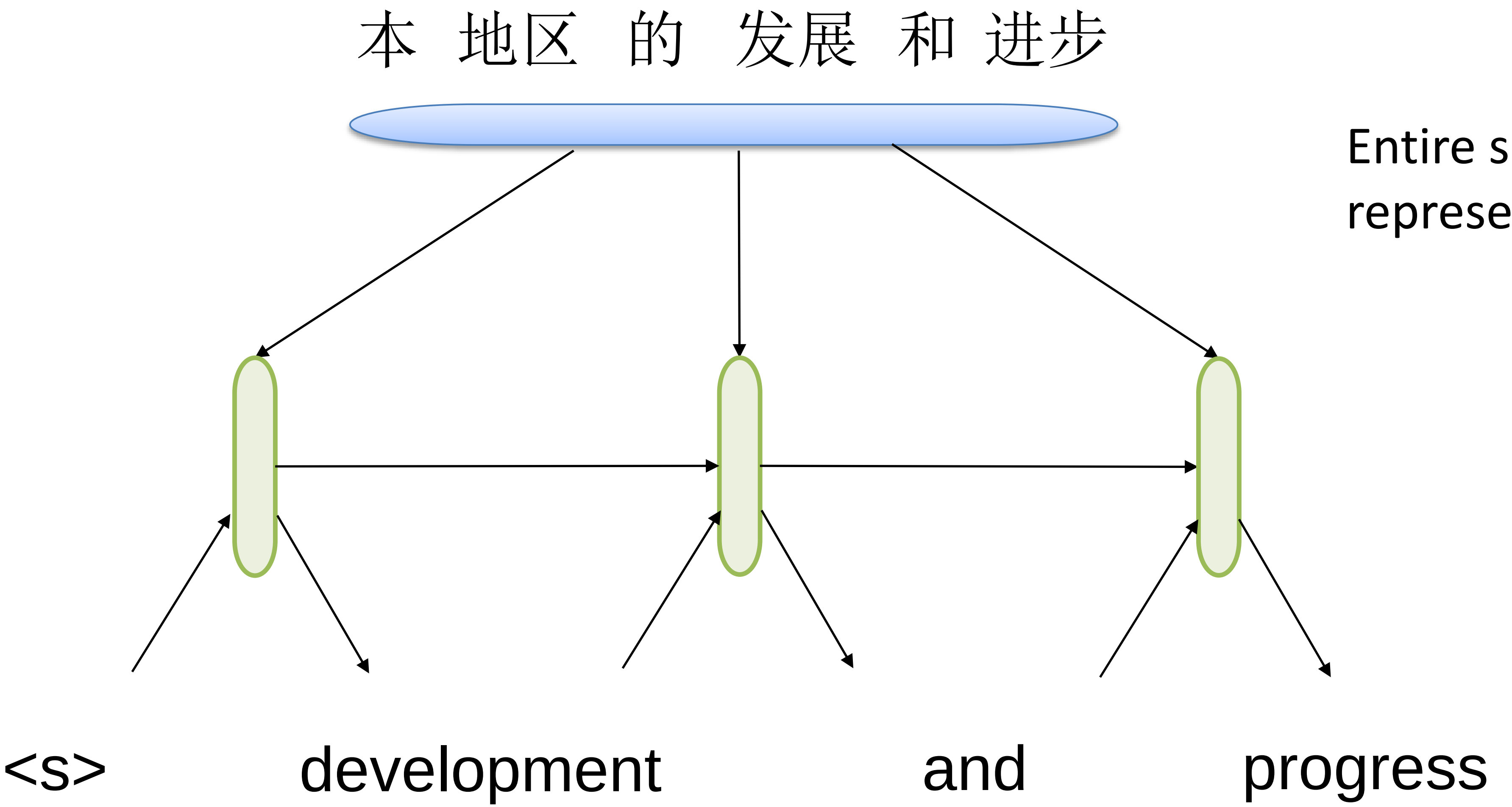

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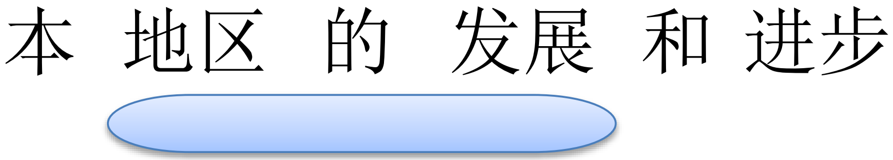

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Source word-window

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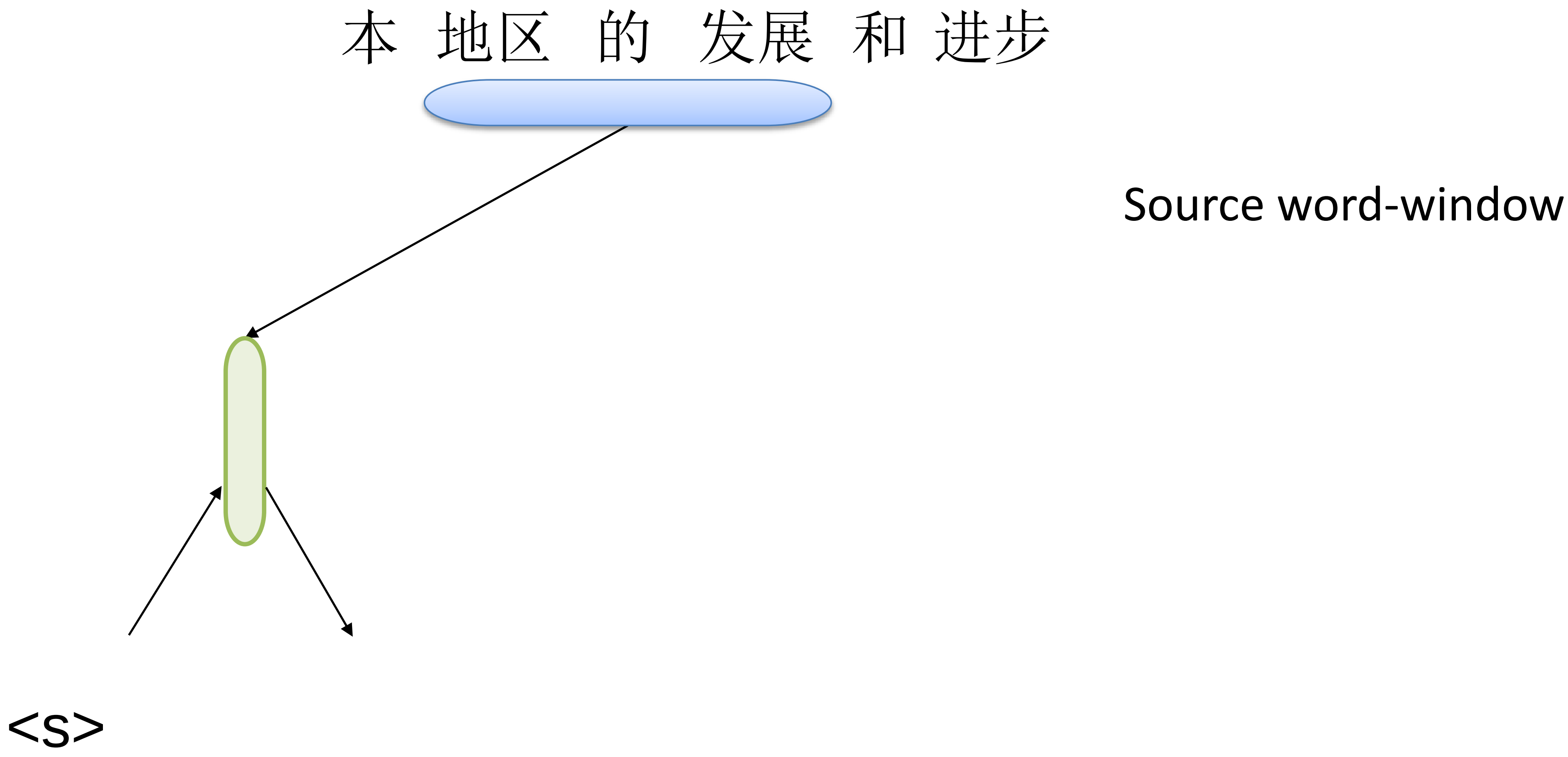

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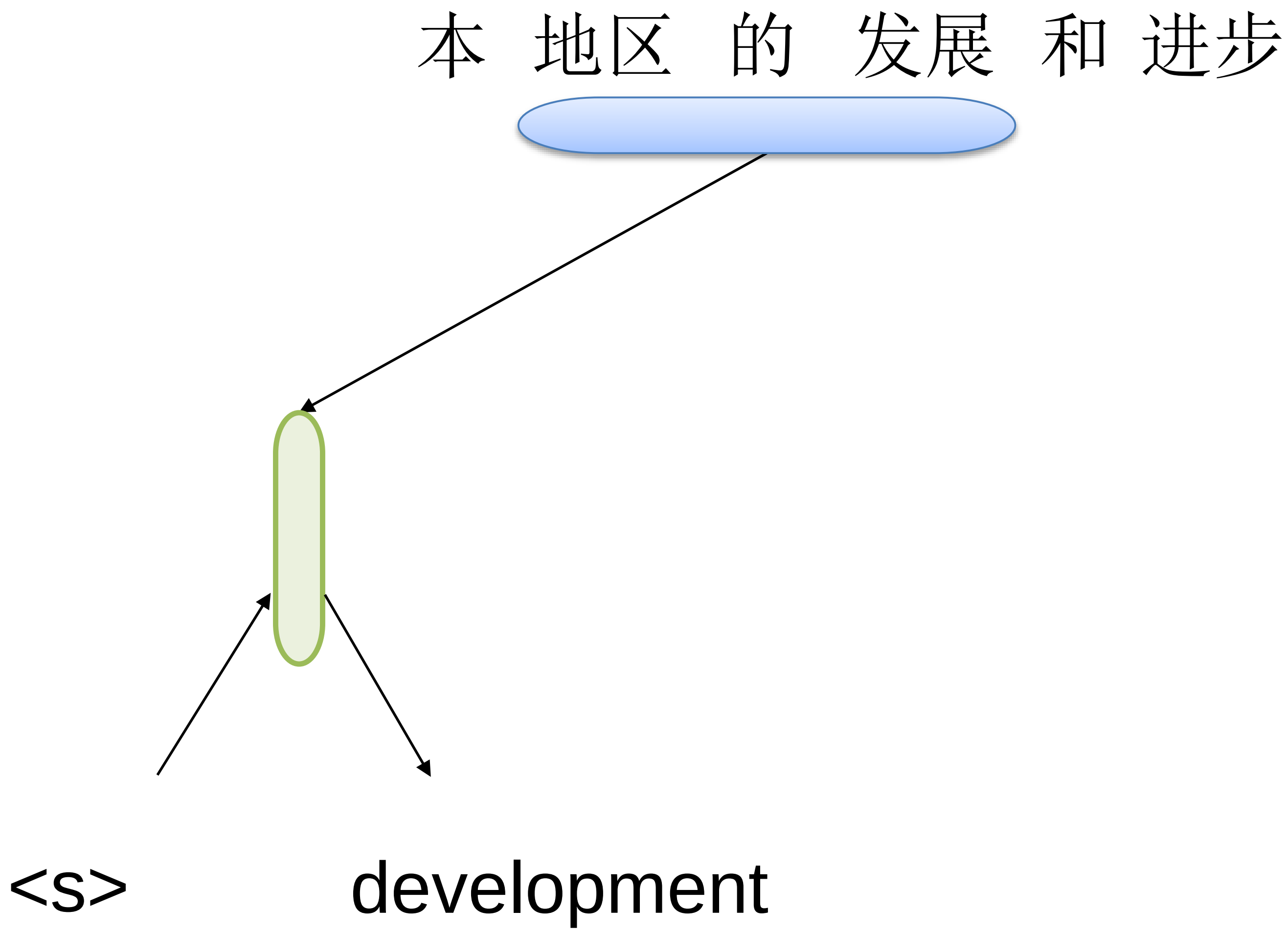

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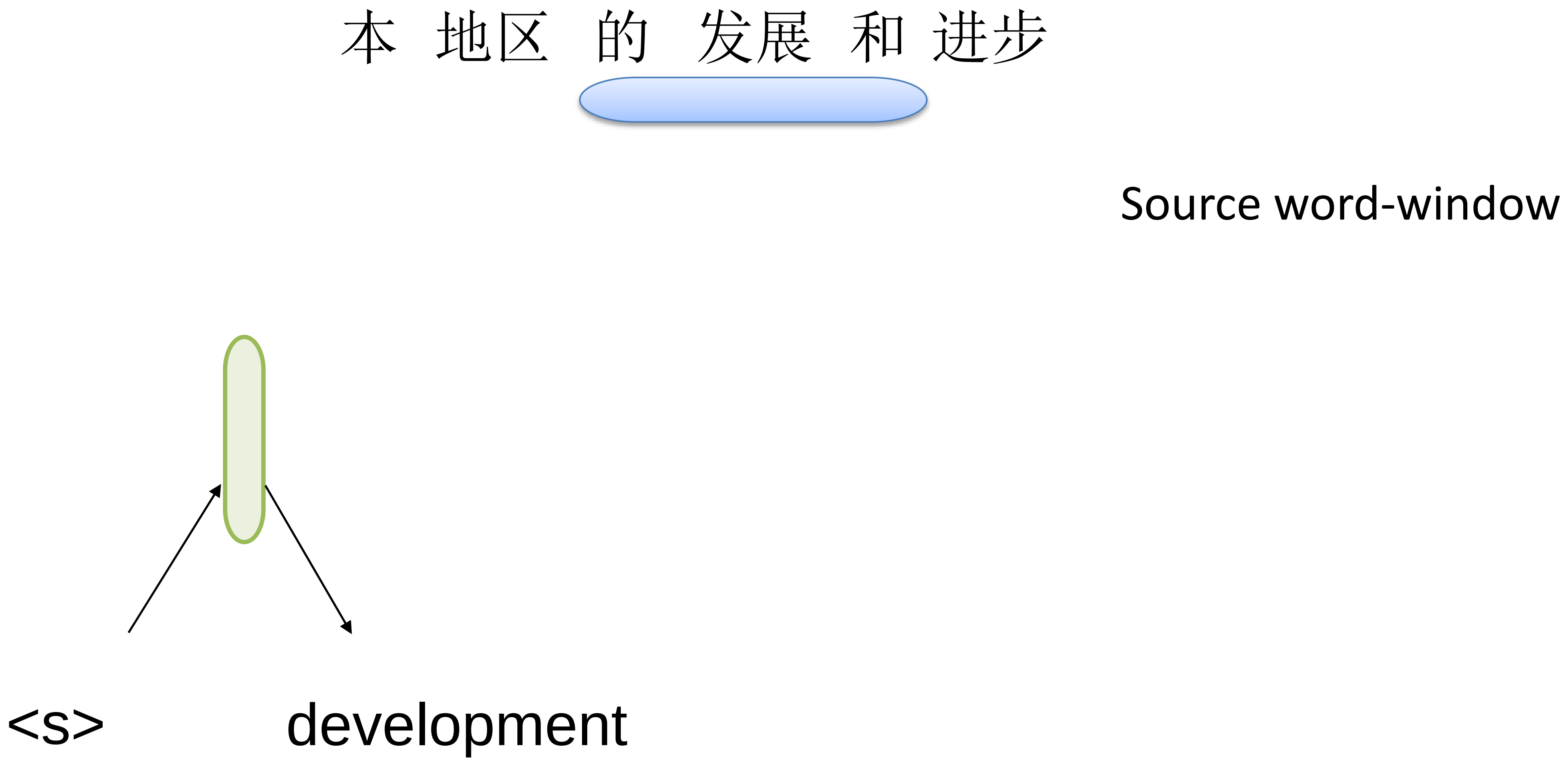

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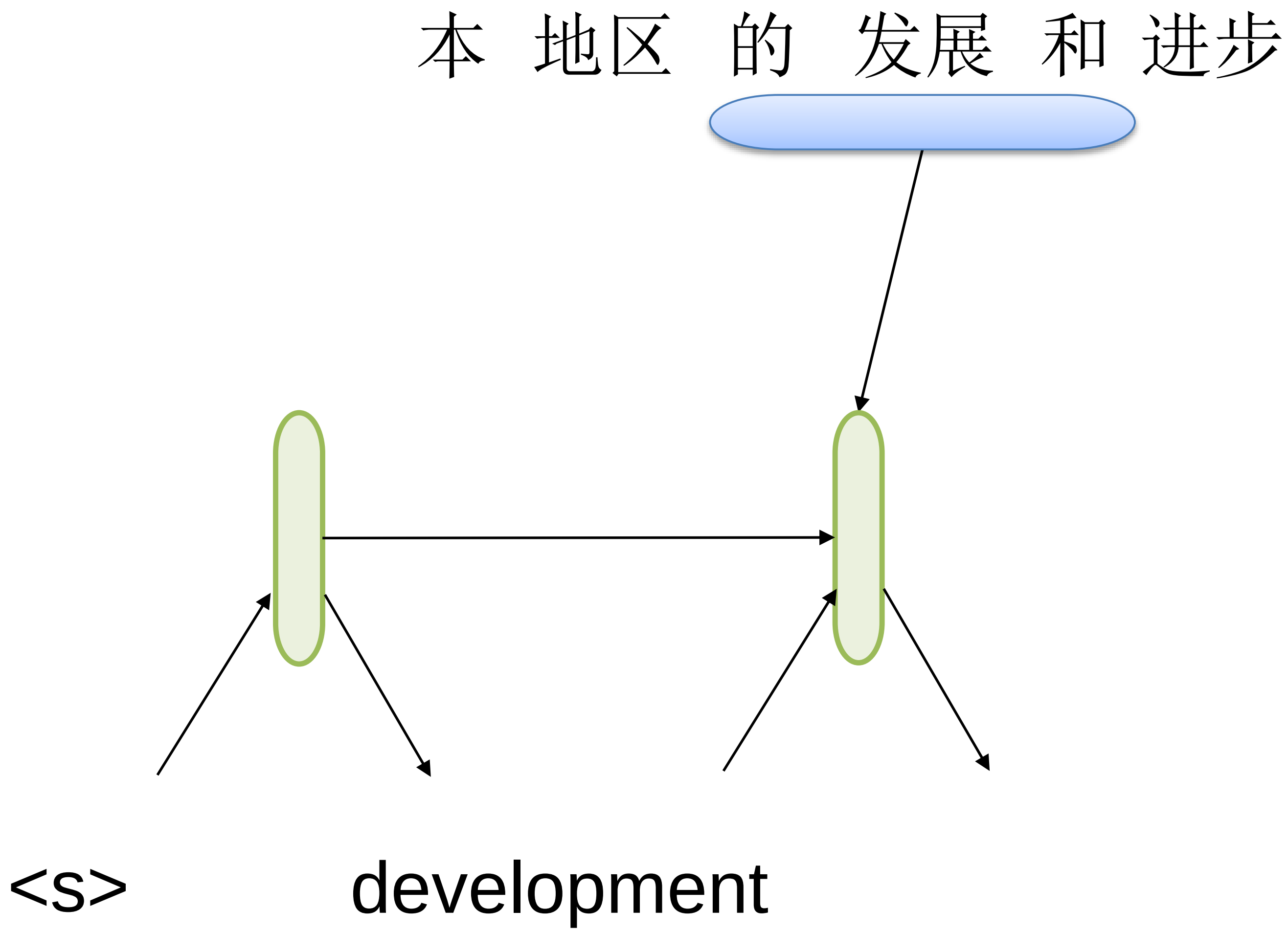

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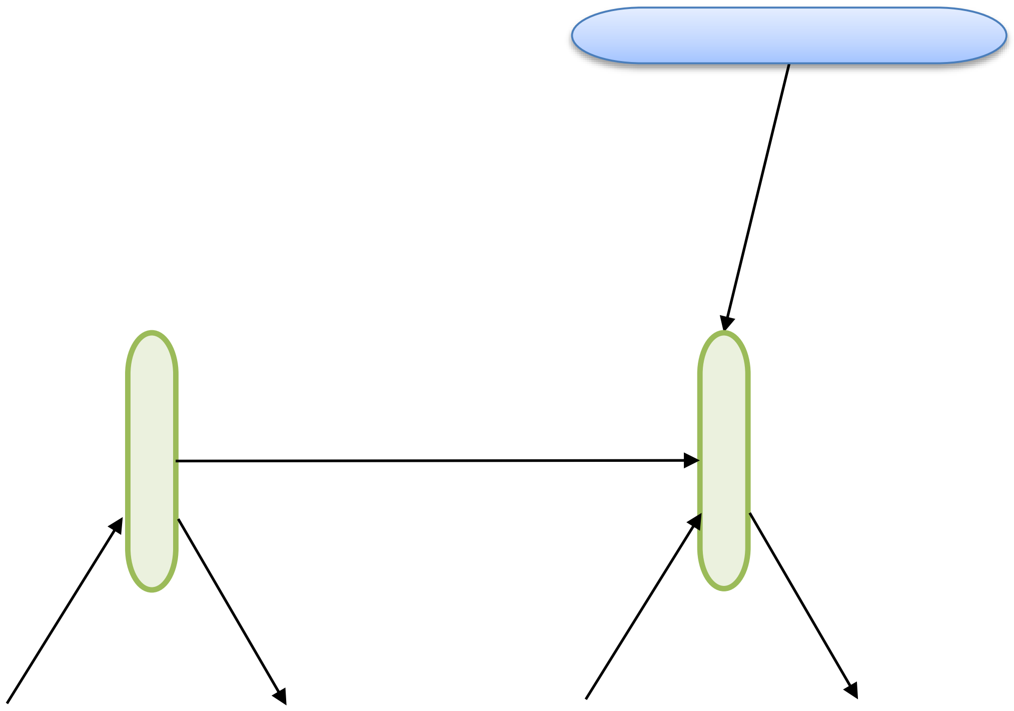

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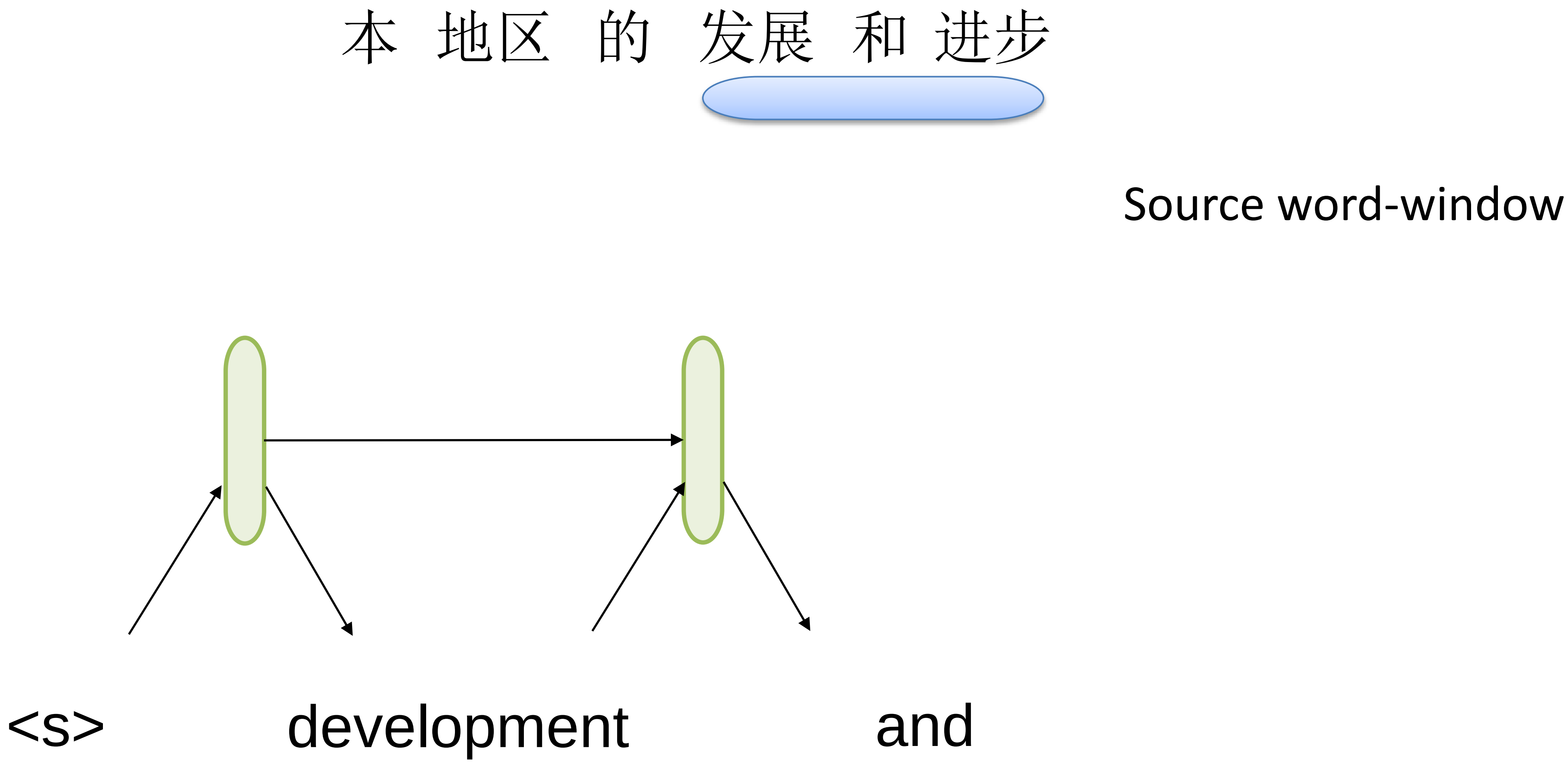

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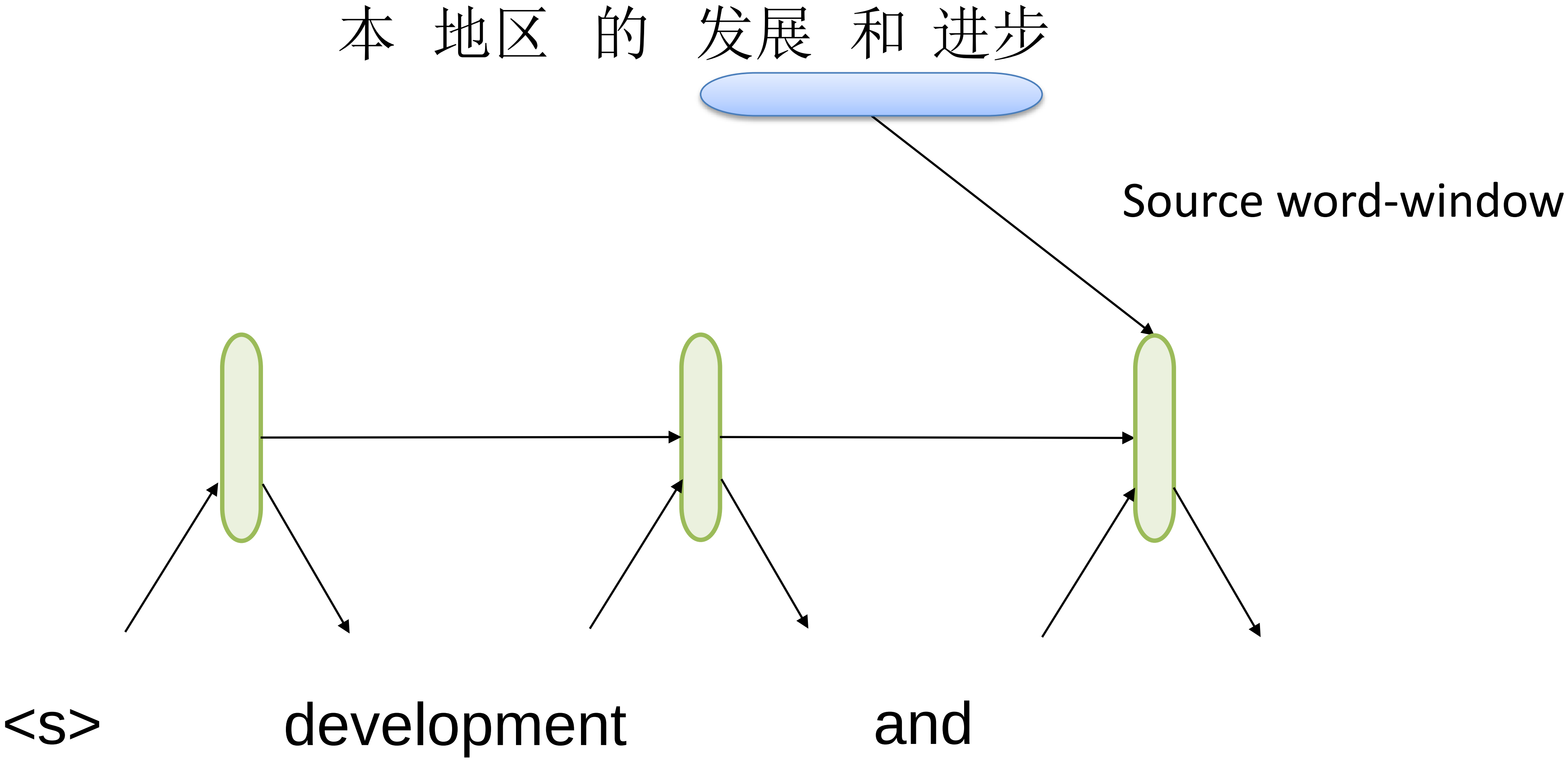

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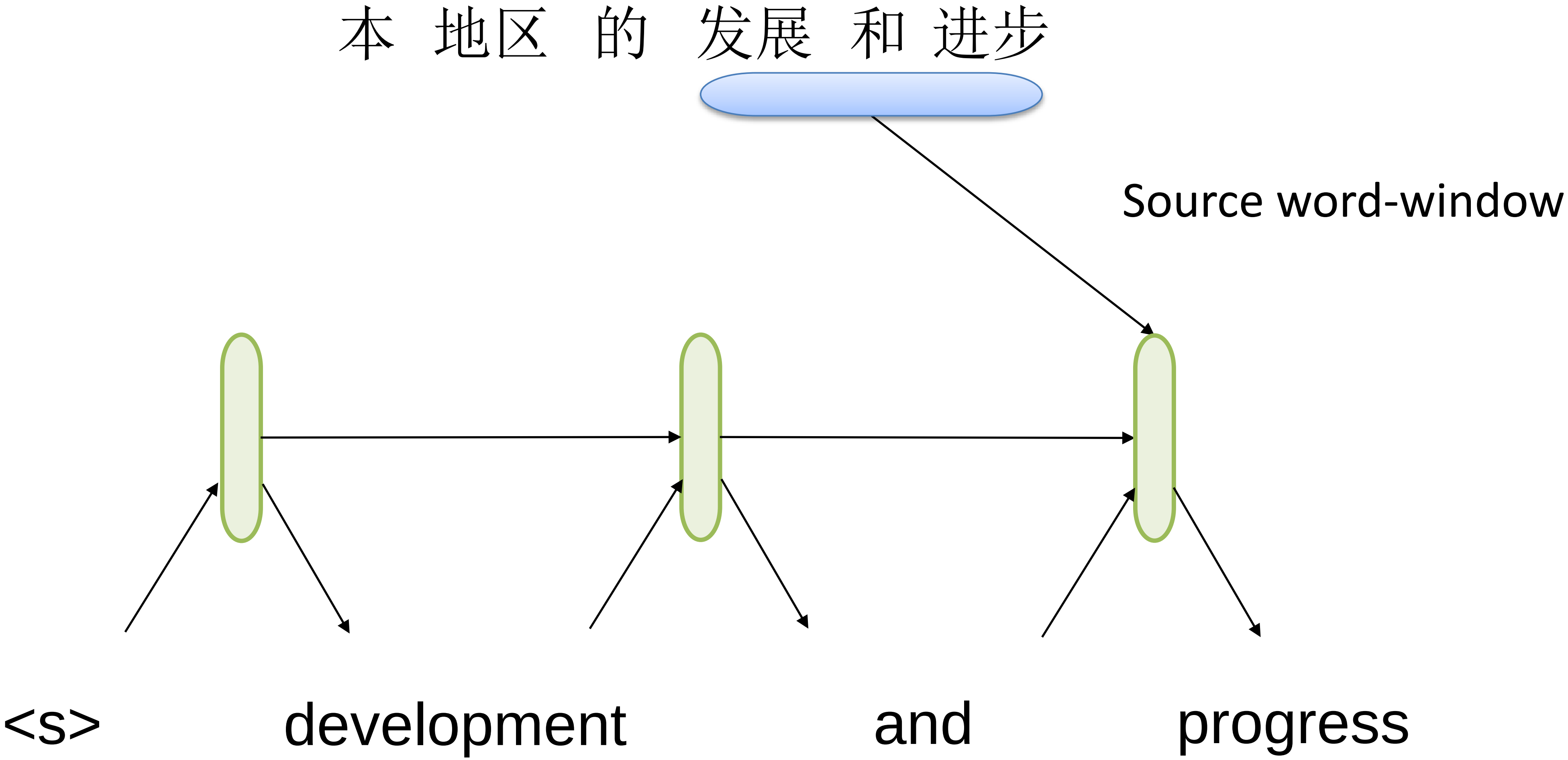
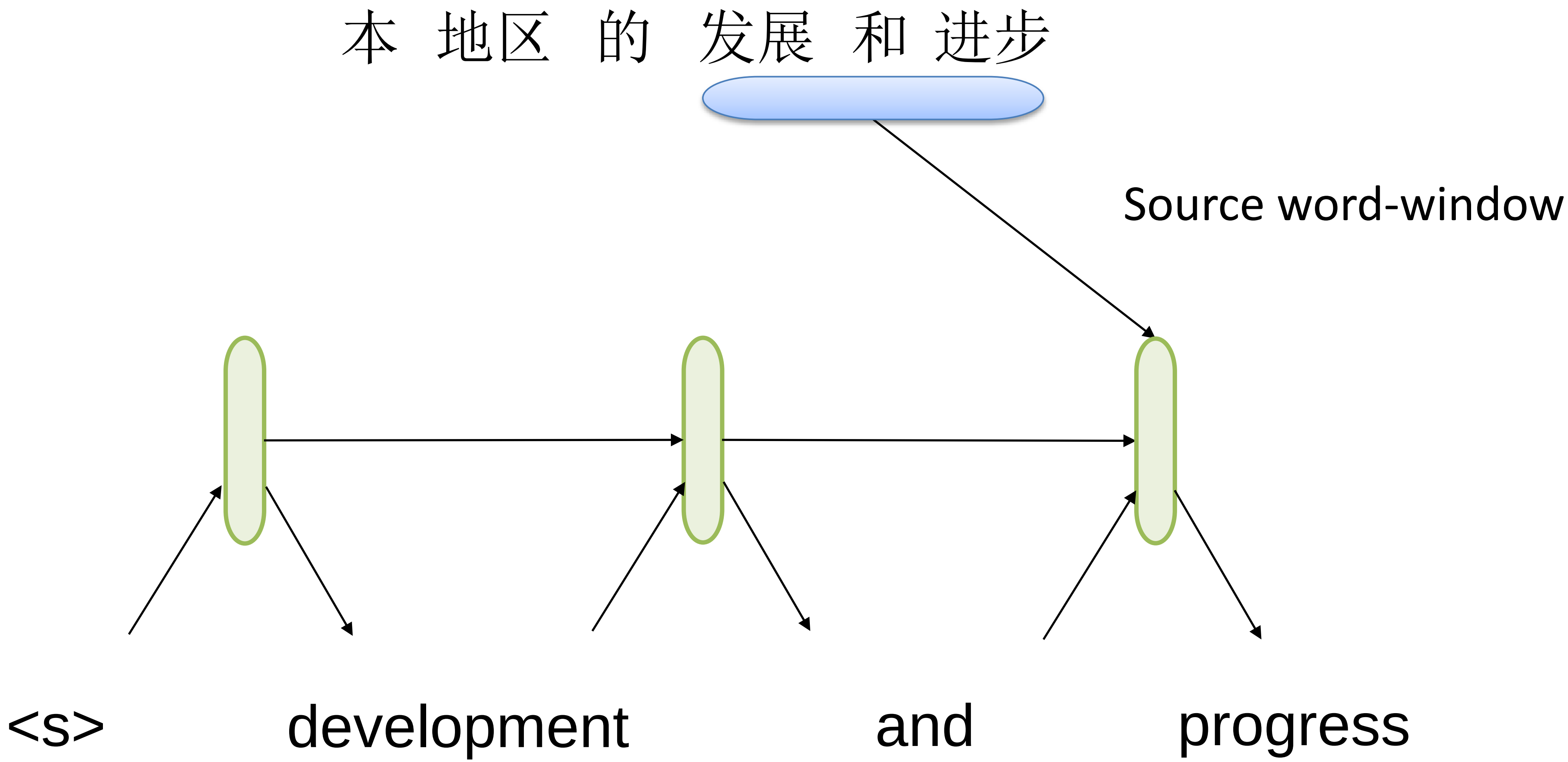
Source word-window

<s> development and

Recurrent Network Joint Model



Recurrent Network Joint Model



Feed-forward nets: Le (2012) & Devlin (2014)

Similar to Kalchbrenner (2013)

Does the joint model learn how to translate?

Experiment: Generate baseline n-best,
remove translation model,
rescore with RNN joint model

WMT 2012 French-English, 100M words, phrase-based baseline

Does the joint model learn how to translate?

Average accuracy over news2010, syscomb2010, news2011

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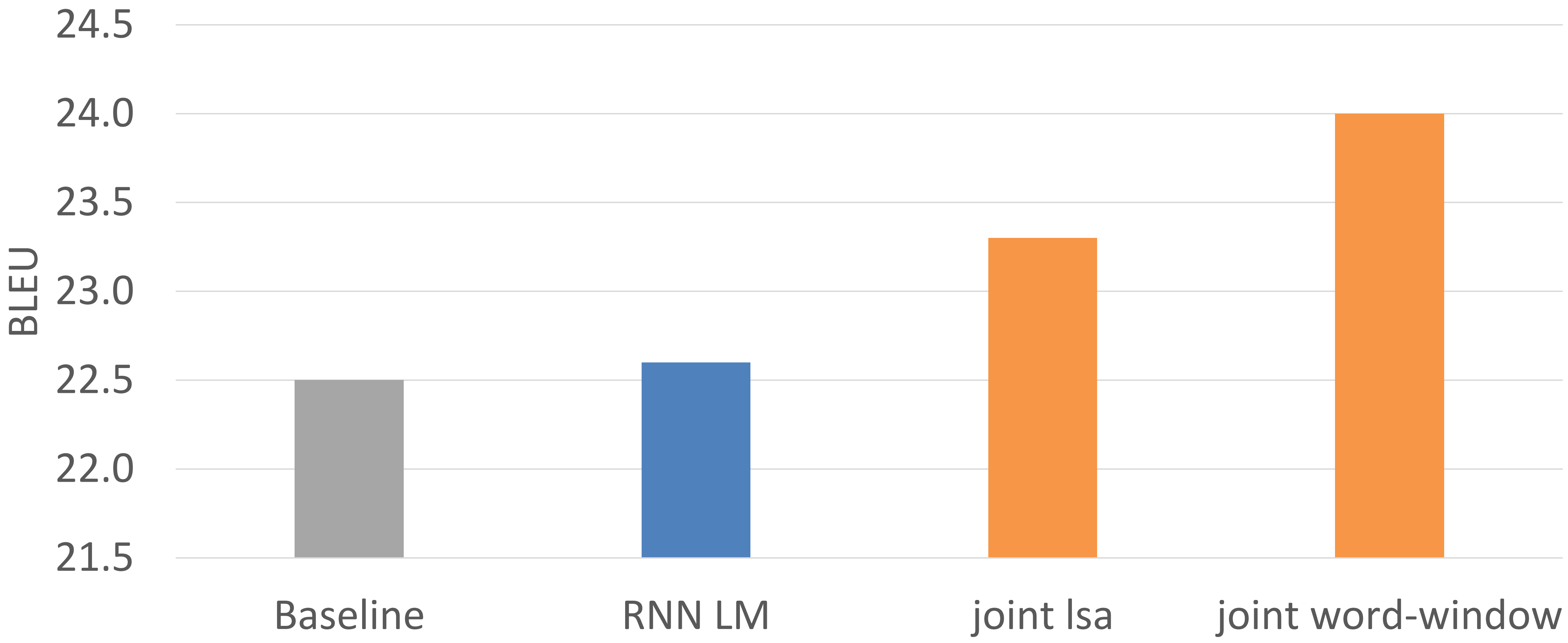

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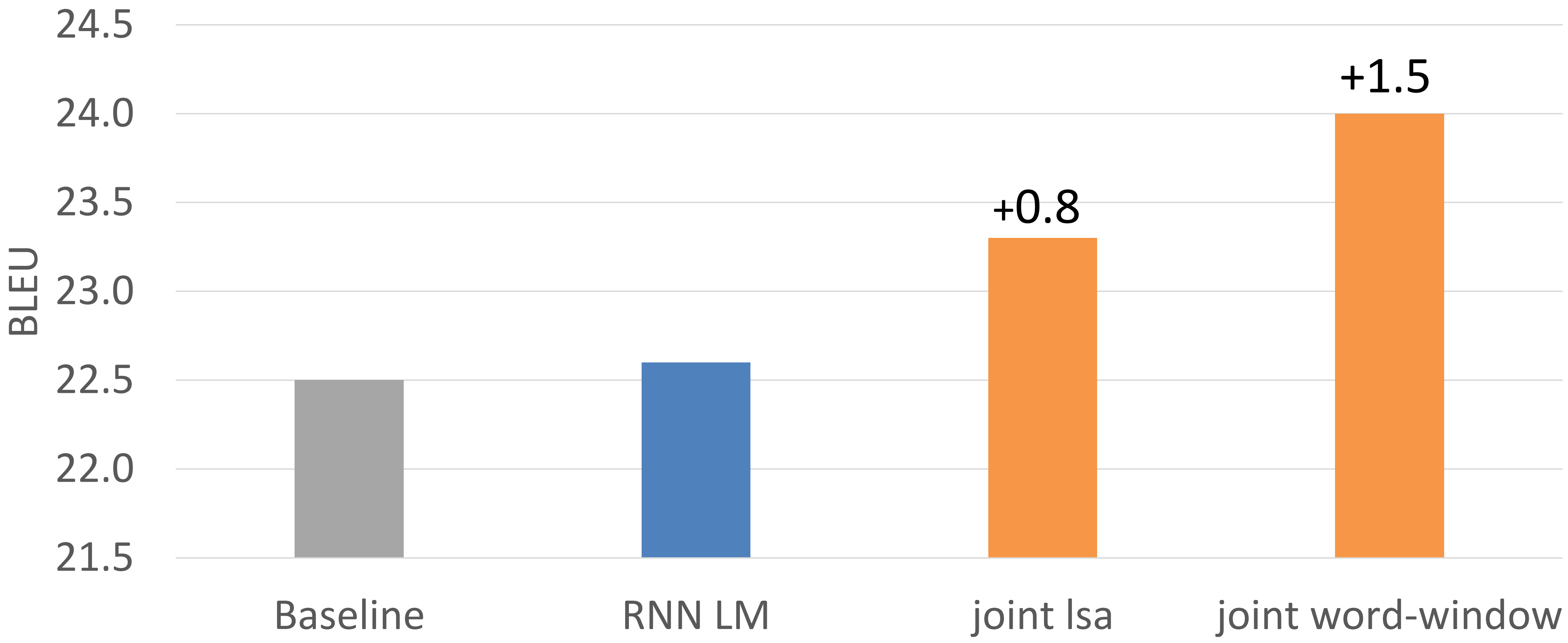

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Improving a phrase-based baseline

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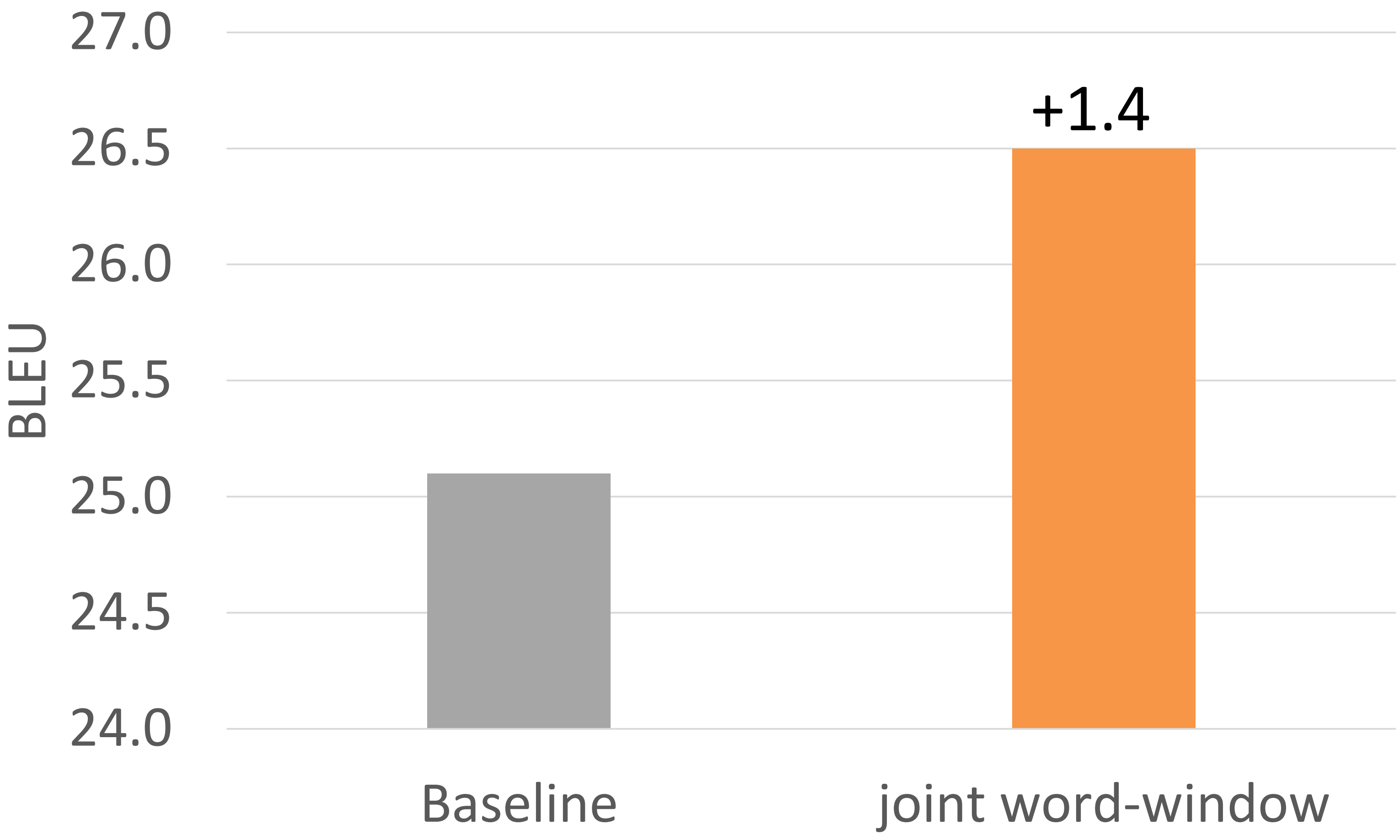


Qualitative Results

src: il aurait fallu 226 voix pour l’ approuver.

ref: its ratification would require 226 votes.

base: it should have been 226 votes to approve it.

rnn: it would have been 226 votes to approve.

Qualitative Results

src: il aurait fallu 226 voix pour l’ approuver.

ref: its ratification would require 226 votes.

base: it should have been 226 votes to approve it.

rnn: it would have been 226 votes to approve.

src: il reste à déterminer les vainqueurs.

ref: it is time to define the winners.

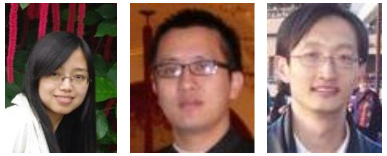
base: it remains to be seen the victors.

rnn: it remains to determine the victors.

Overview

- Recurrent neural network joint models (Auli et al., EMNLP 2013)
  Combined language and translation modeling

- Minimum translation modeling with recurrent nets (Hu et al., EACL 2014)
  Sequence models over bilingual units



- Training recurrent nets (Auli & Gao, ACL 2014)
  Expected BLEU training for neural network translation models

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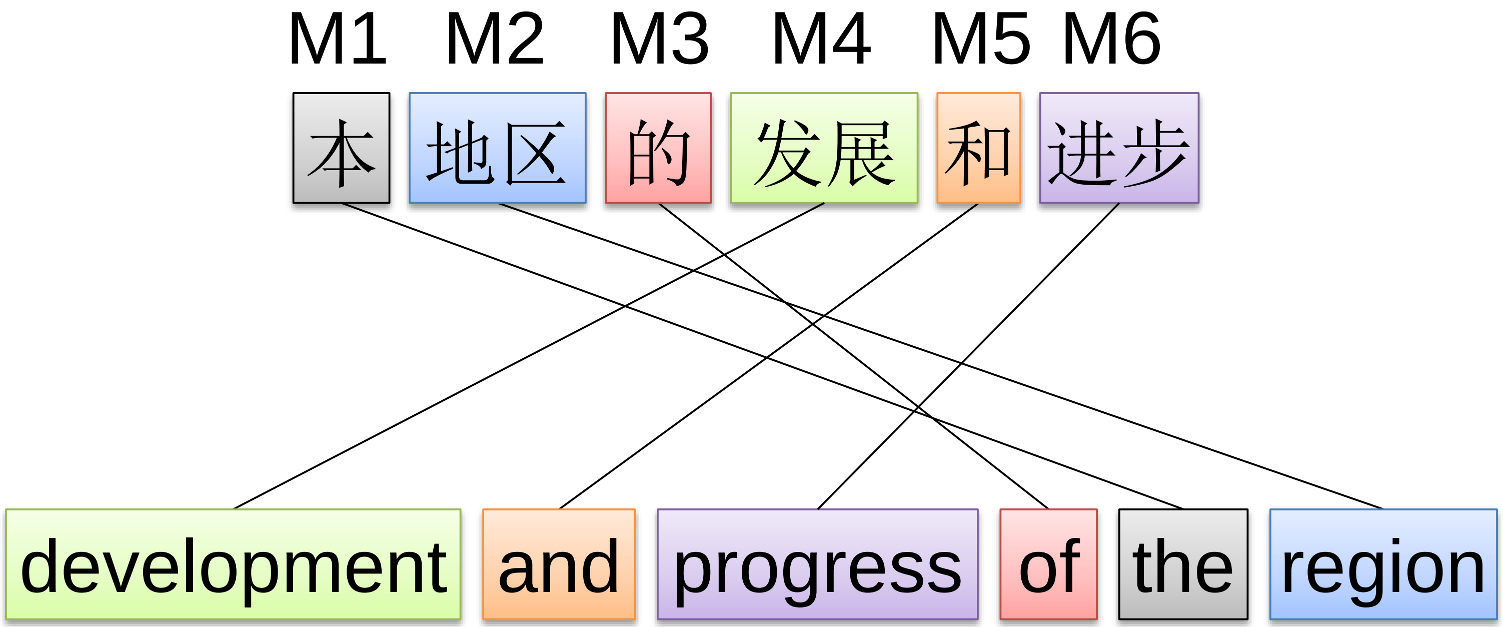
  Training millions of linear ordering features with expected BLEU

本 地区 的 发展 和 进步

development and progress of the region


M1
M2
M3
M4
M5
M6
本
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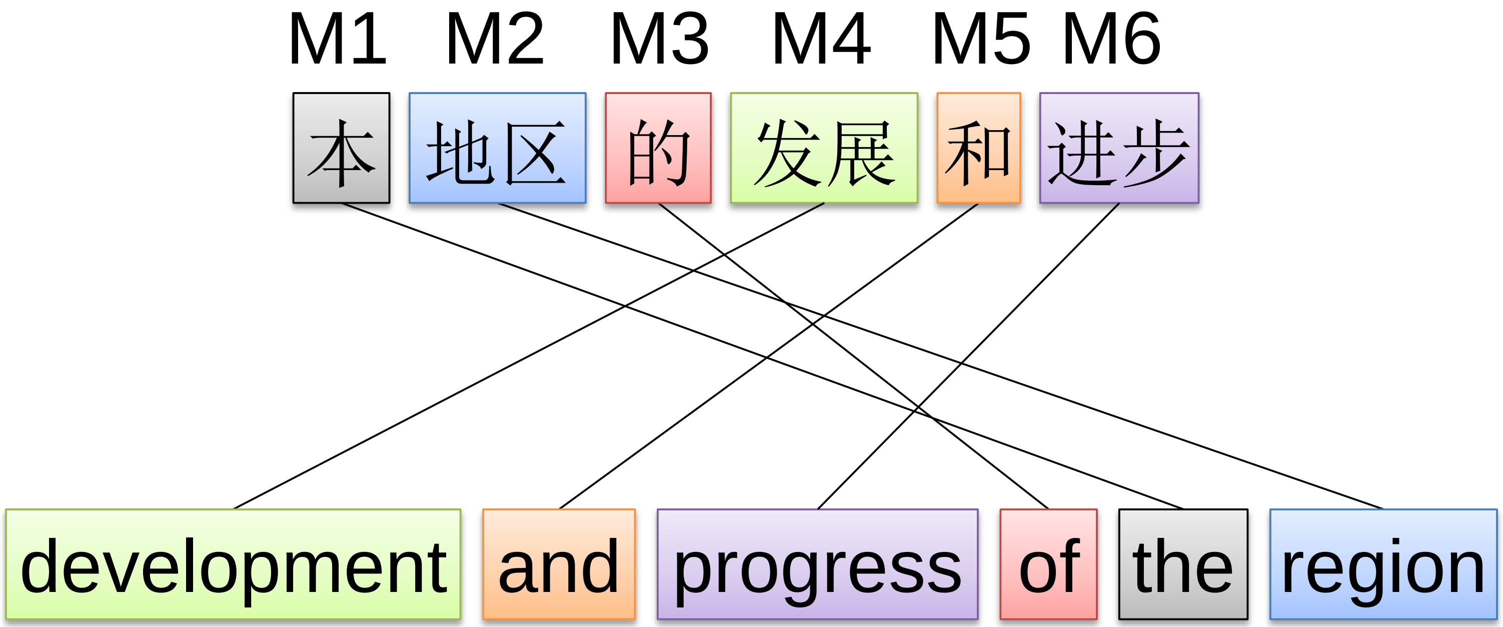

M1 M2 M3 M4 M5 M6

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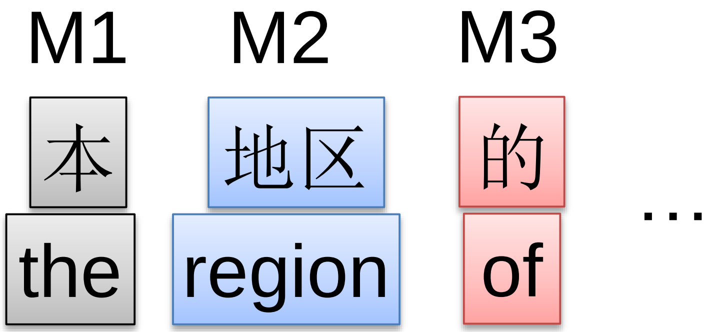


M1 M2 M3

本 地区 的

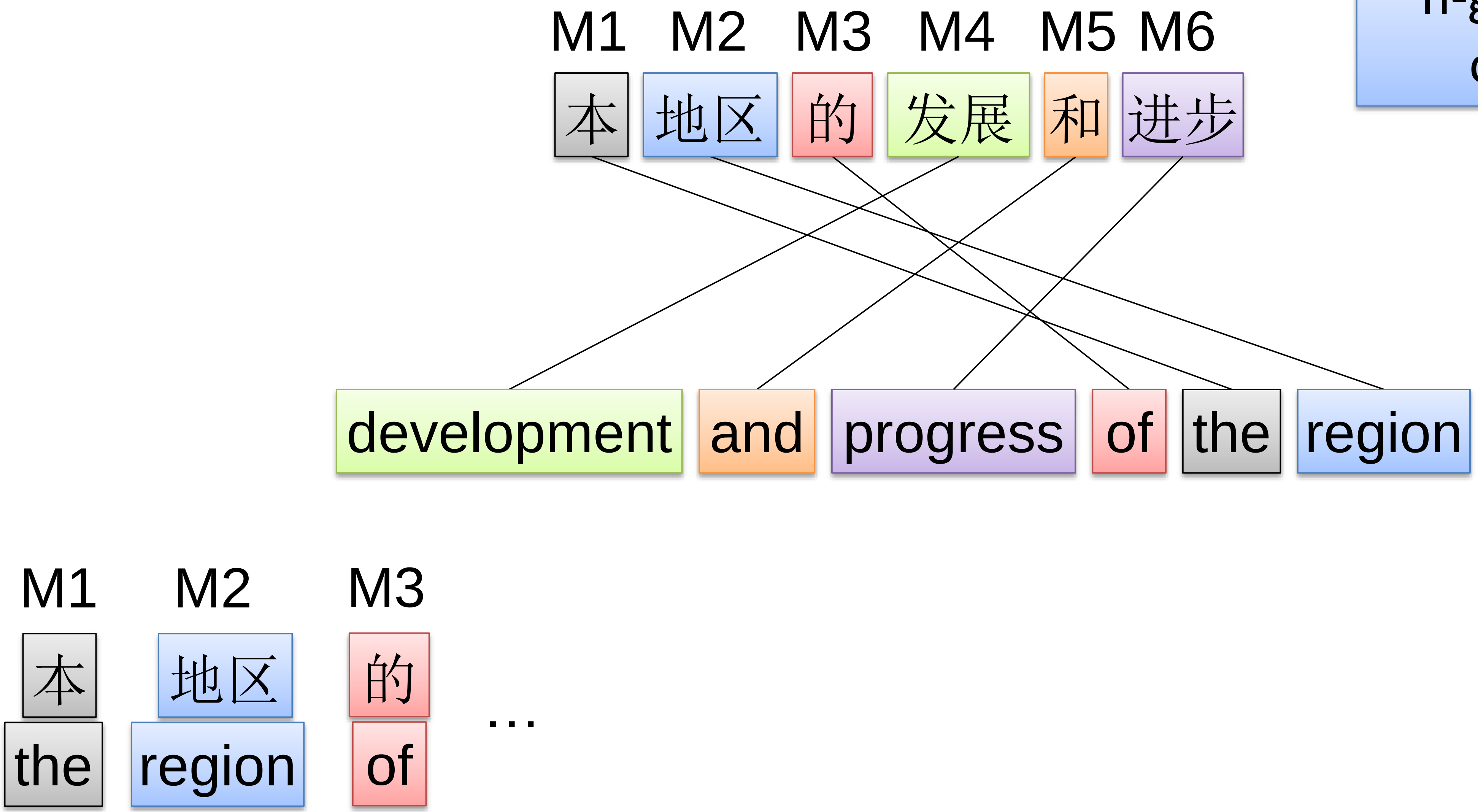
the region of

…

Banchs et al. (2005)

Quirk & Menezes (2006)

n-gram models over MTUs



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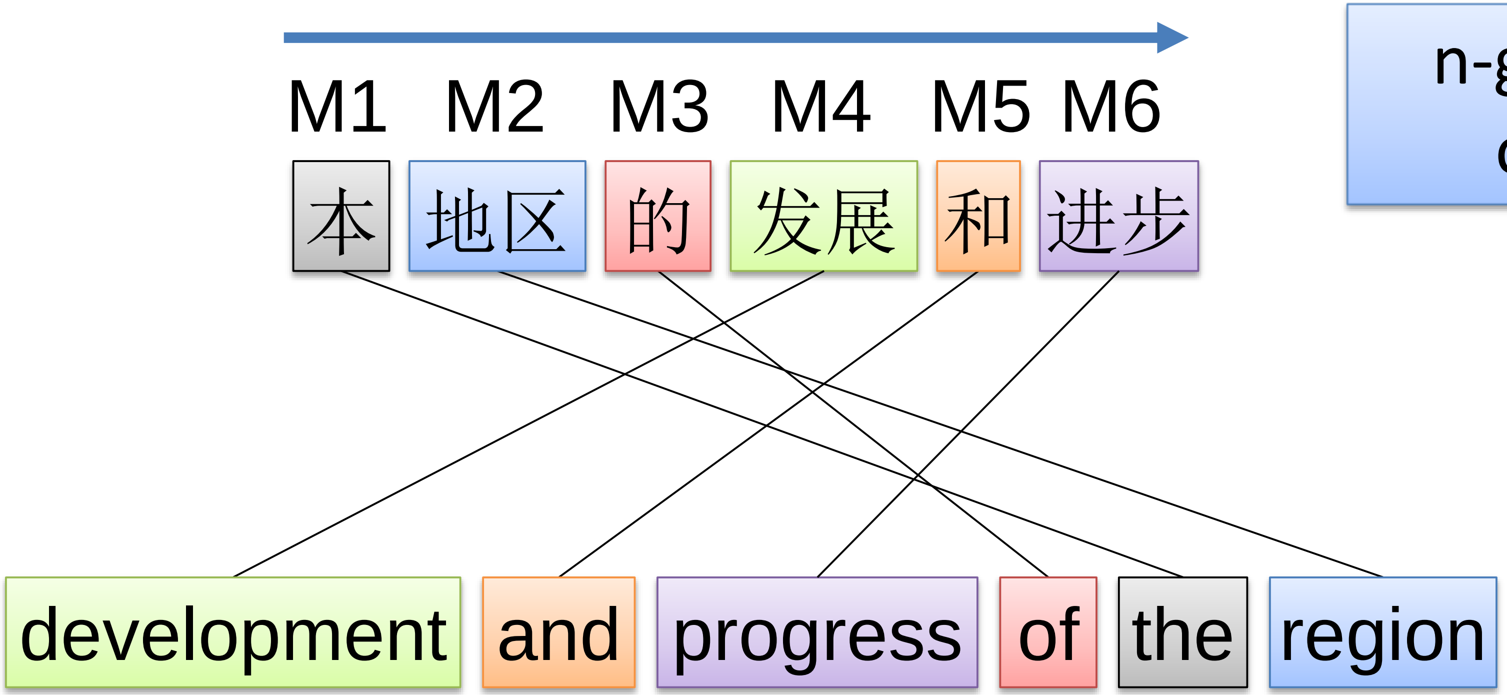

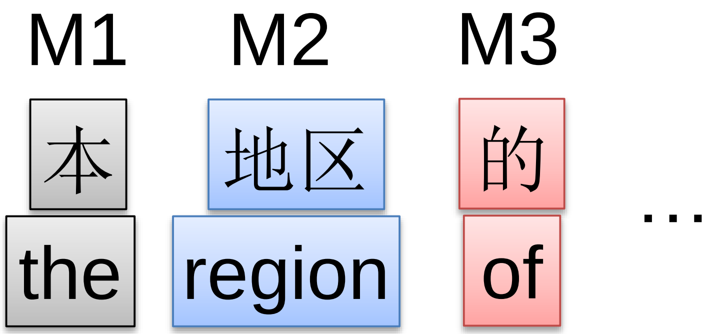

Source order: p(M1) p(M2|M1) p(M3|M1,M2) …

Banchs et al. (2005)

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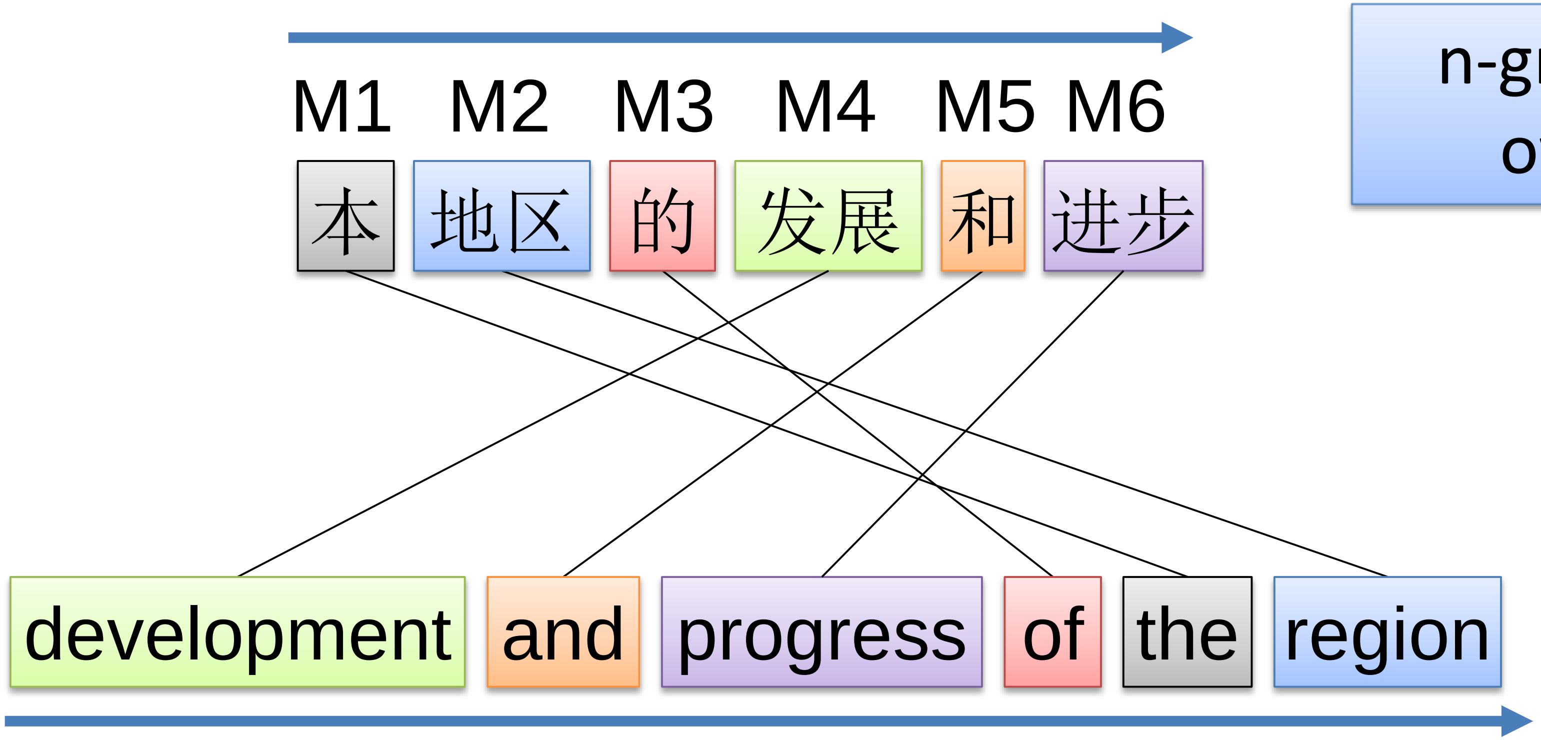

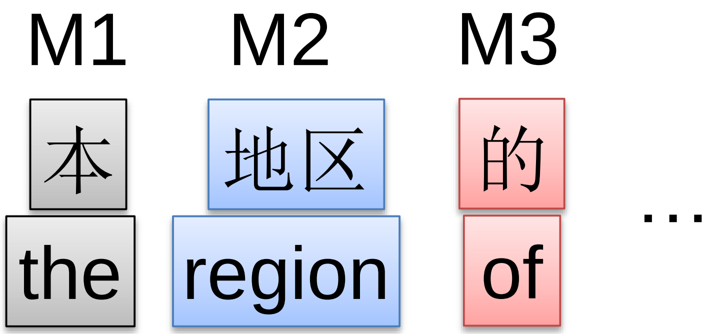

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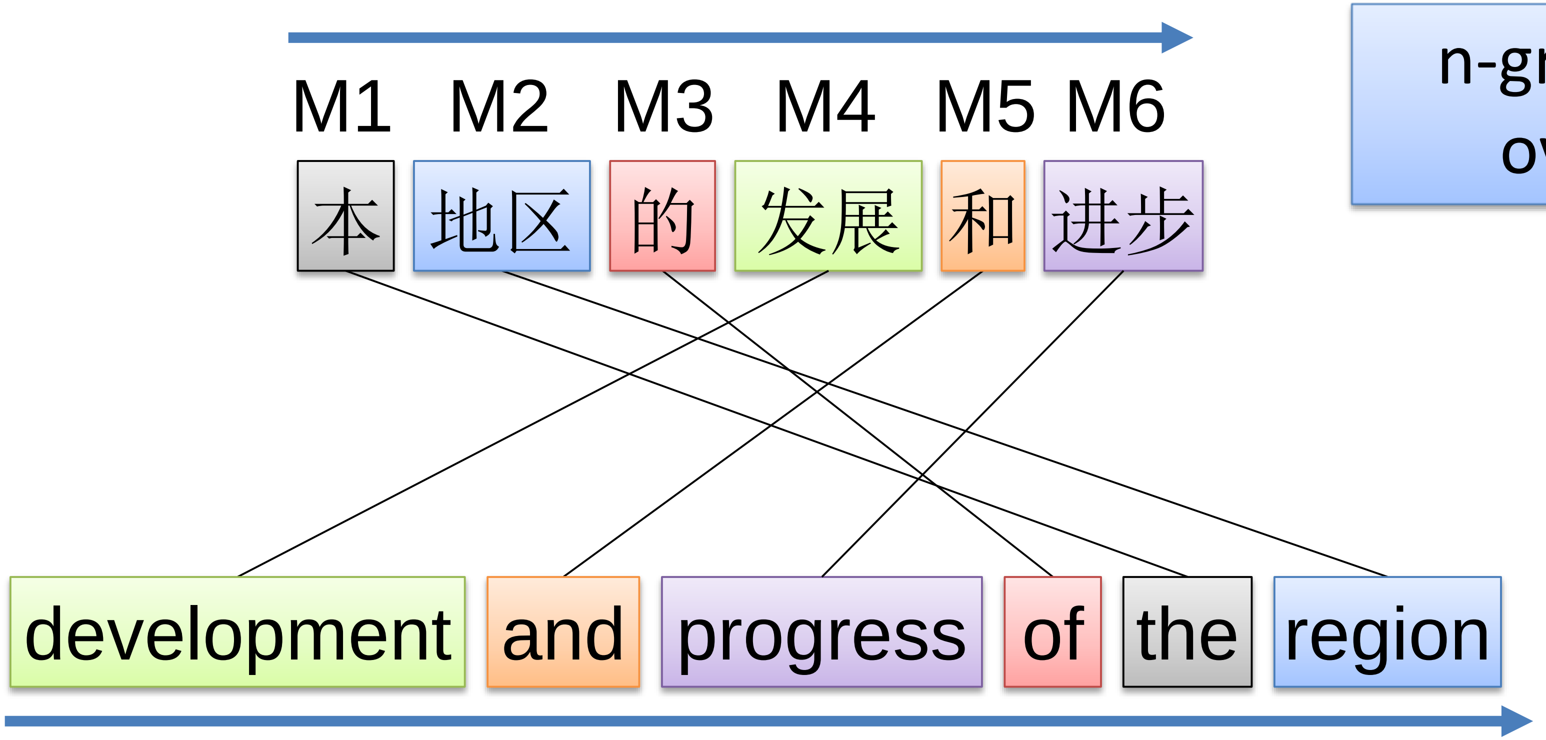

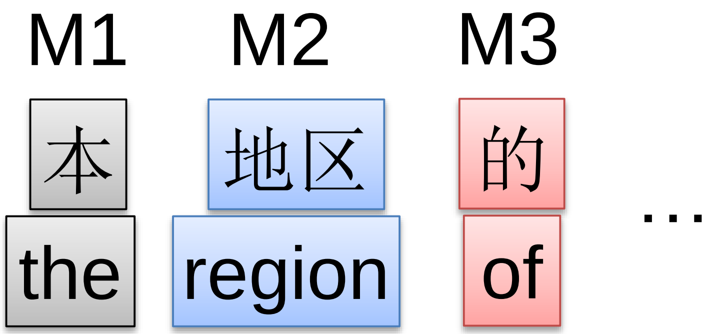

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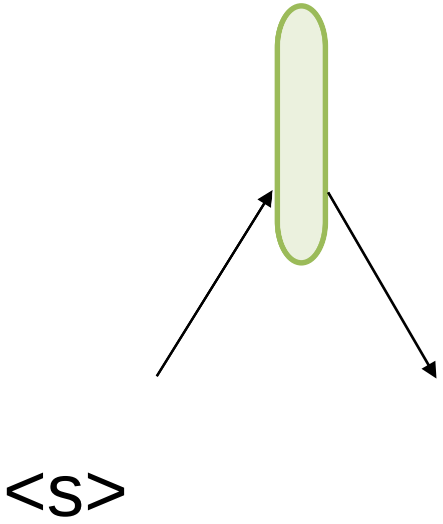
Model 1: Recurrent Atomic MTU



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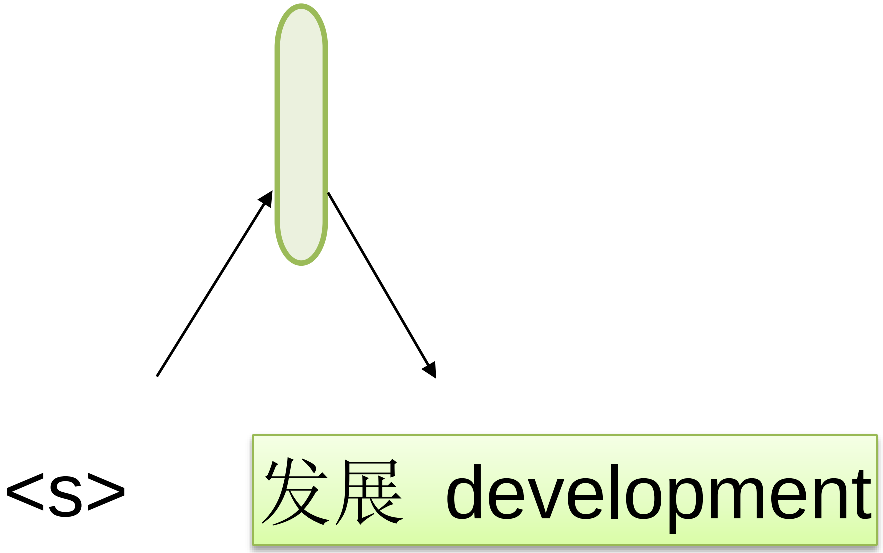

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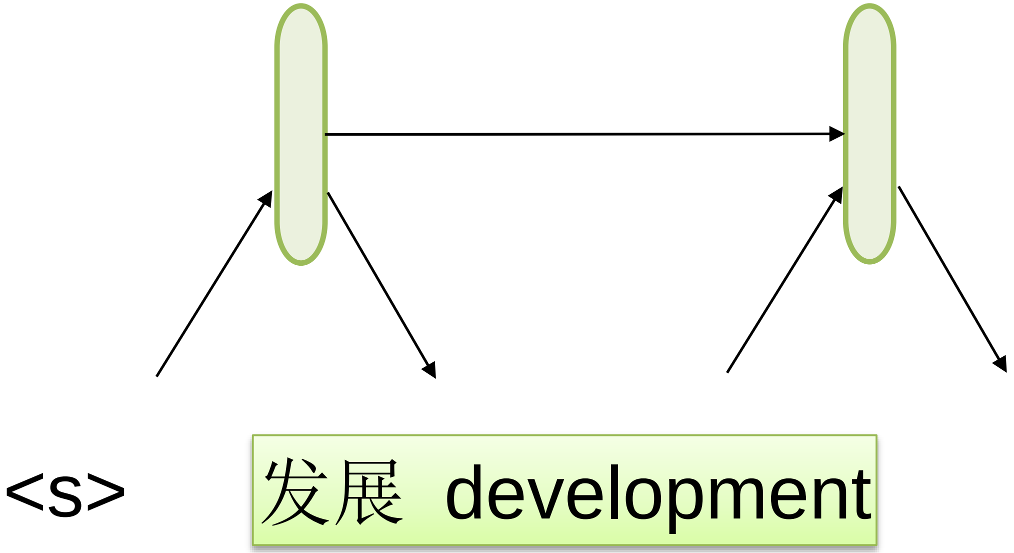

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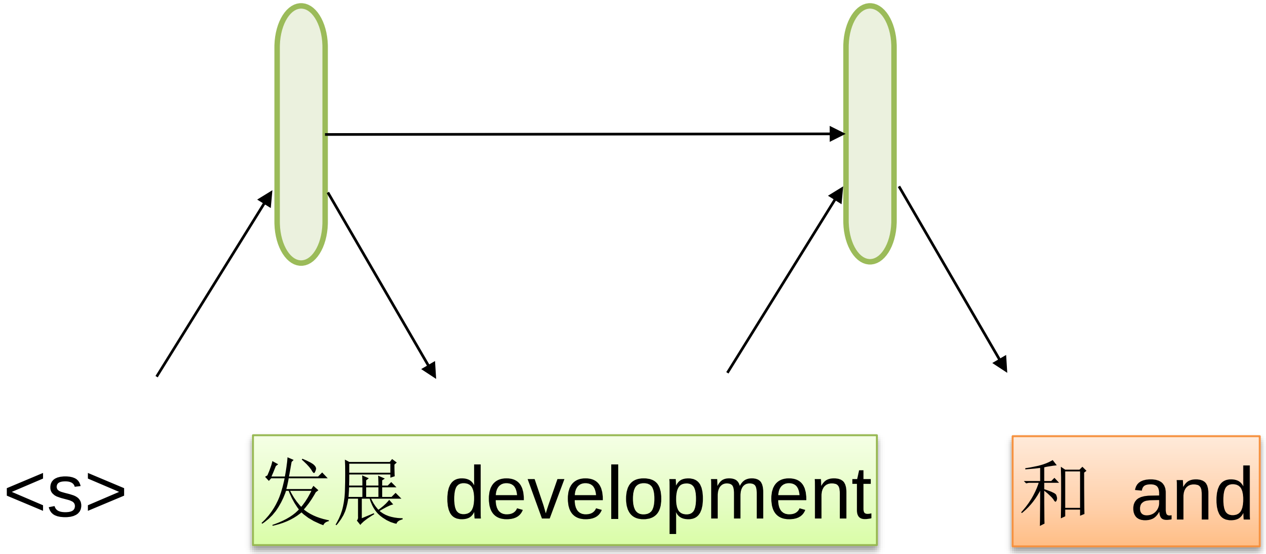

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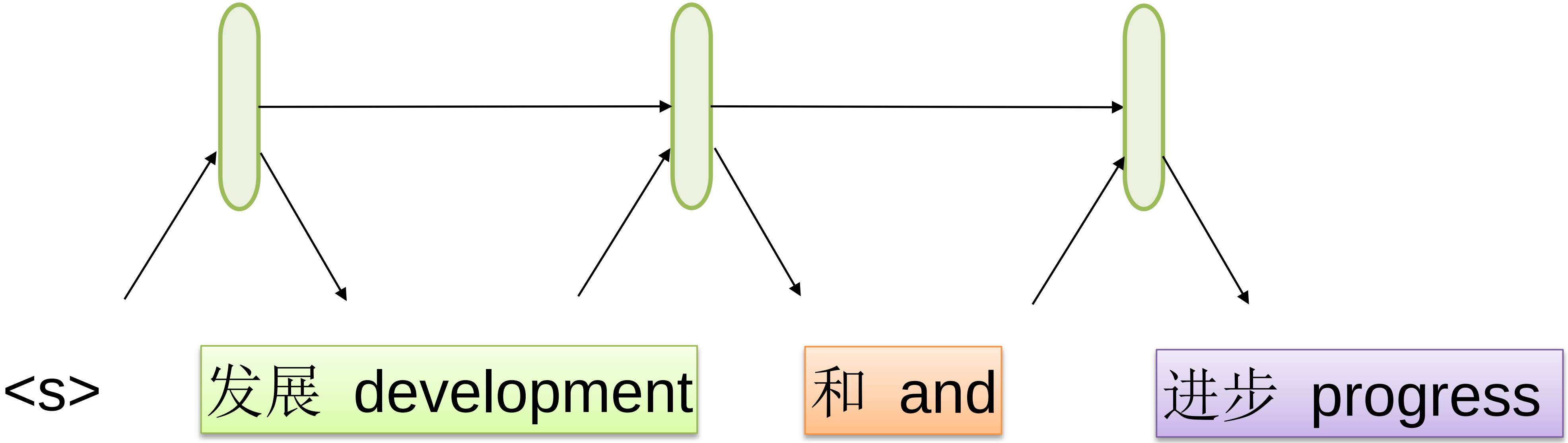
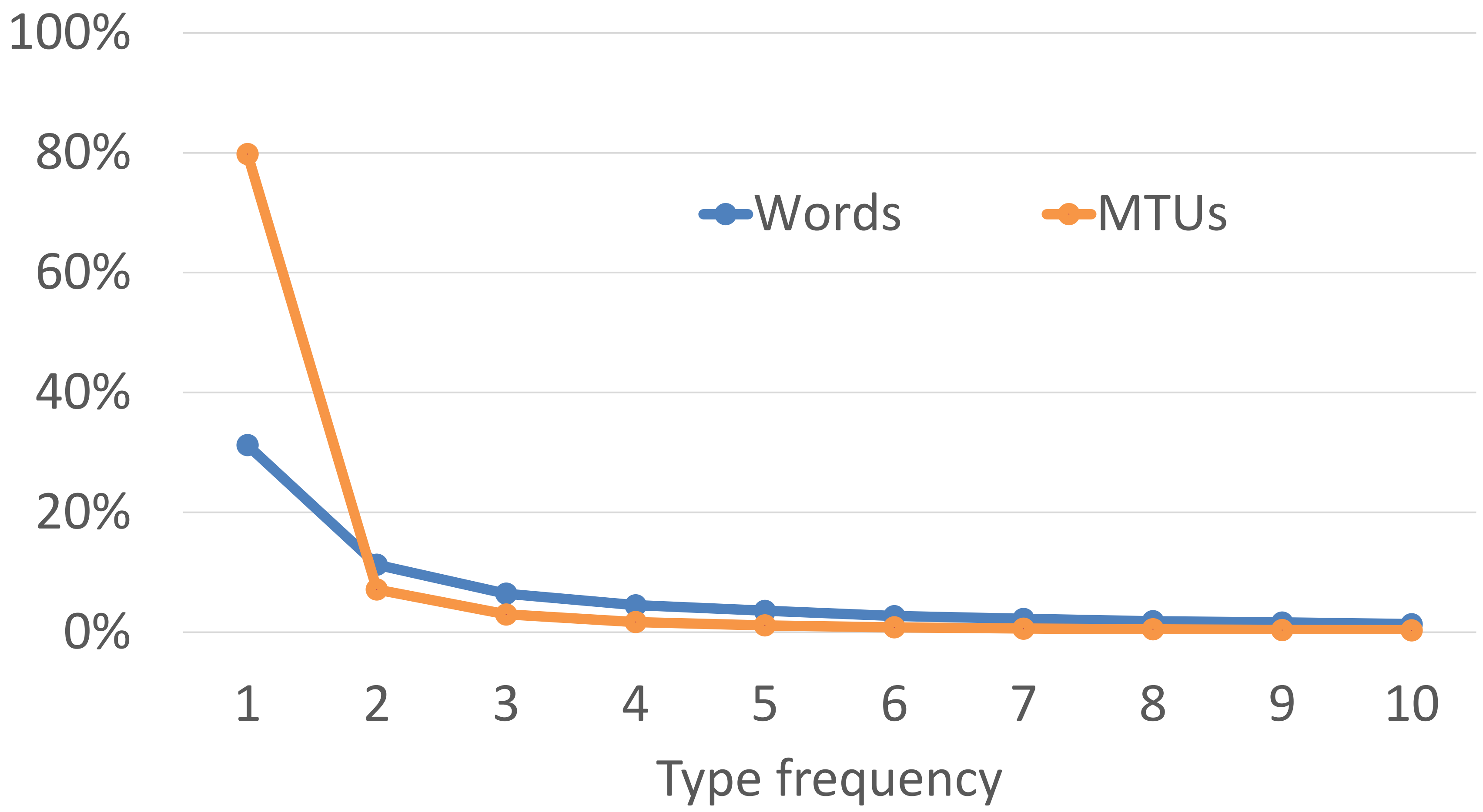


Data sparsity



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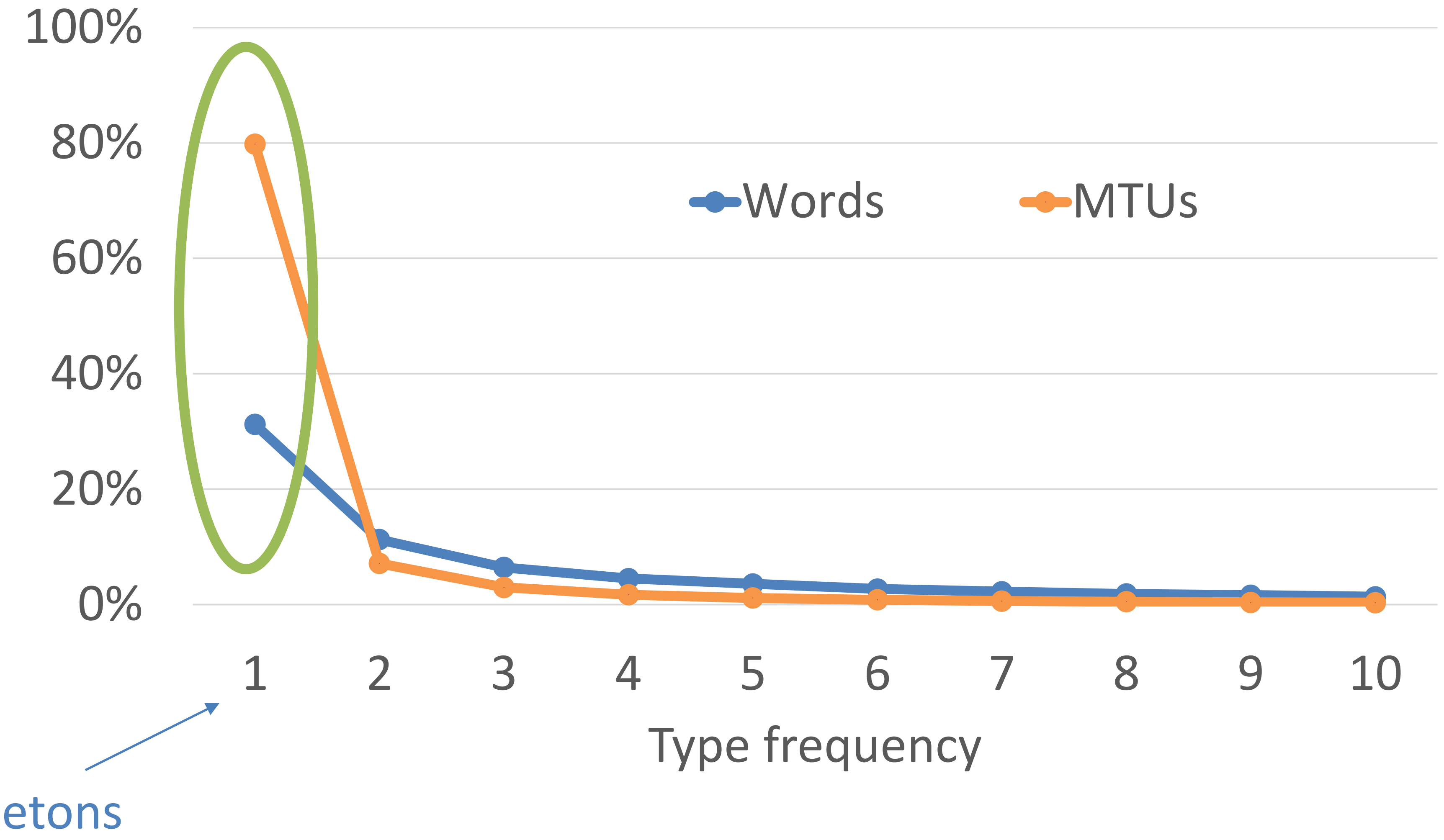
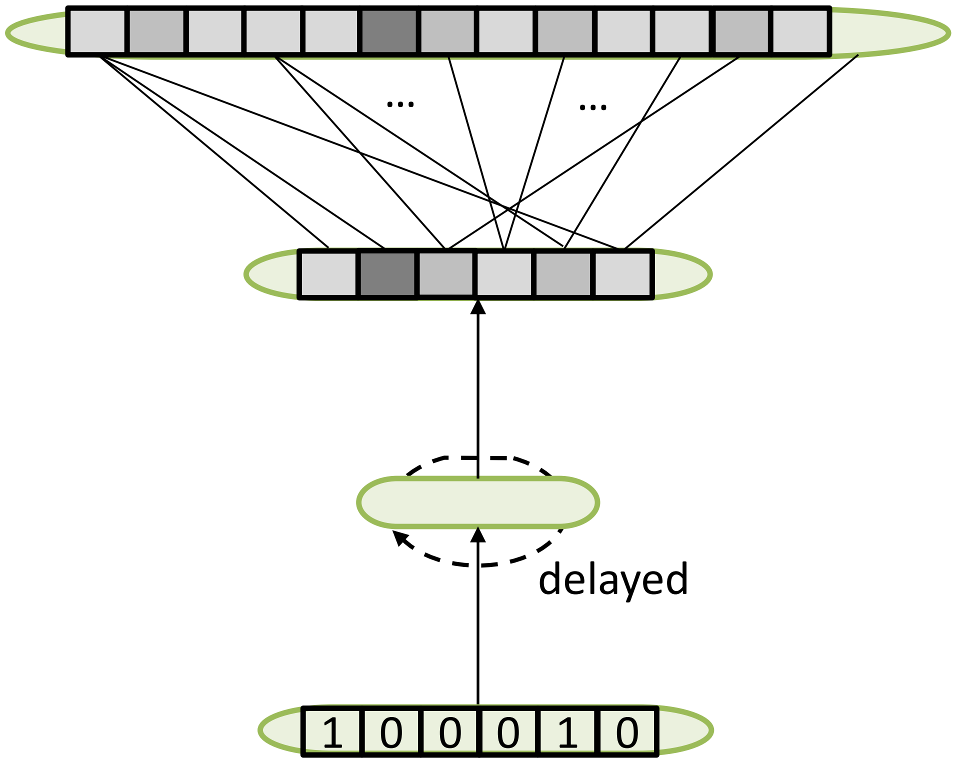


Model 2: Bag of Words MTU



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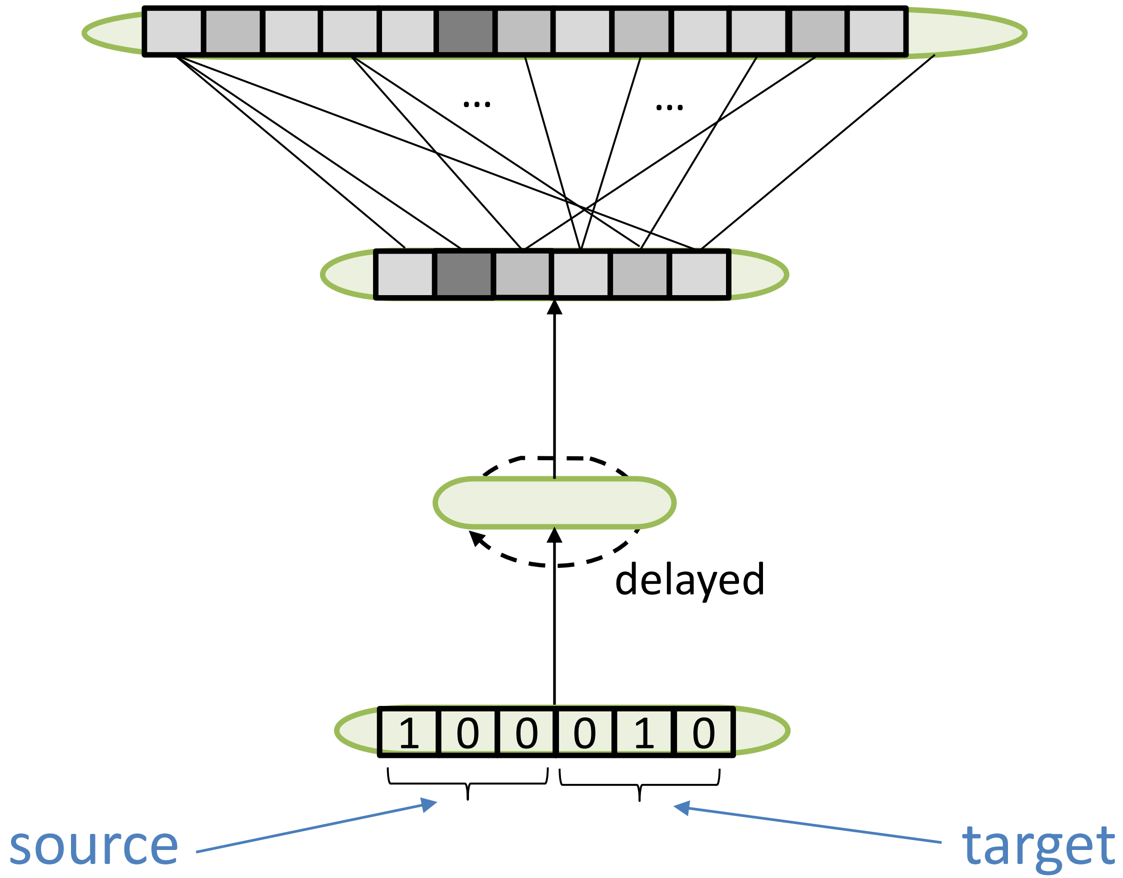

Input: previous MTU as
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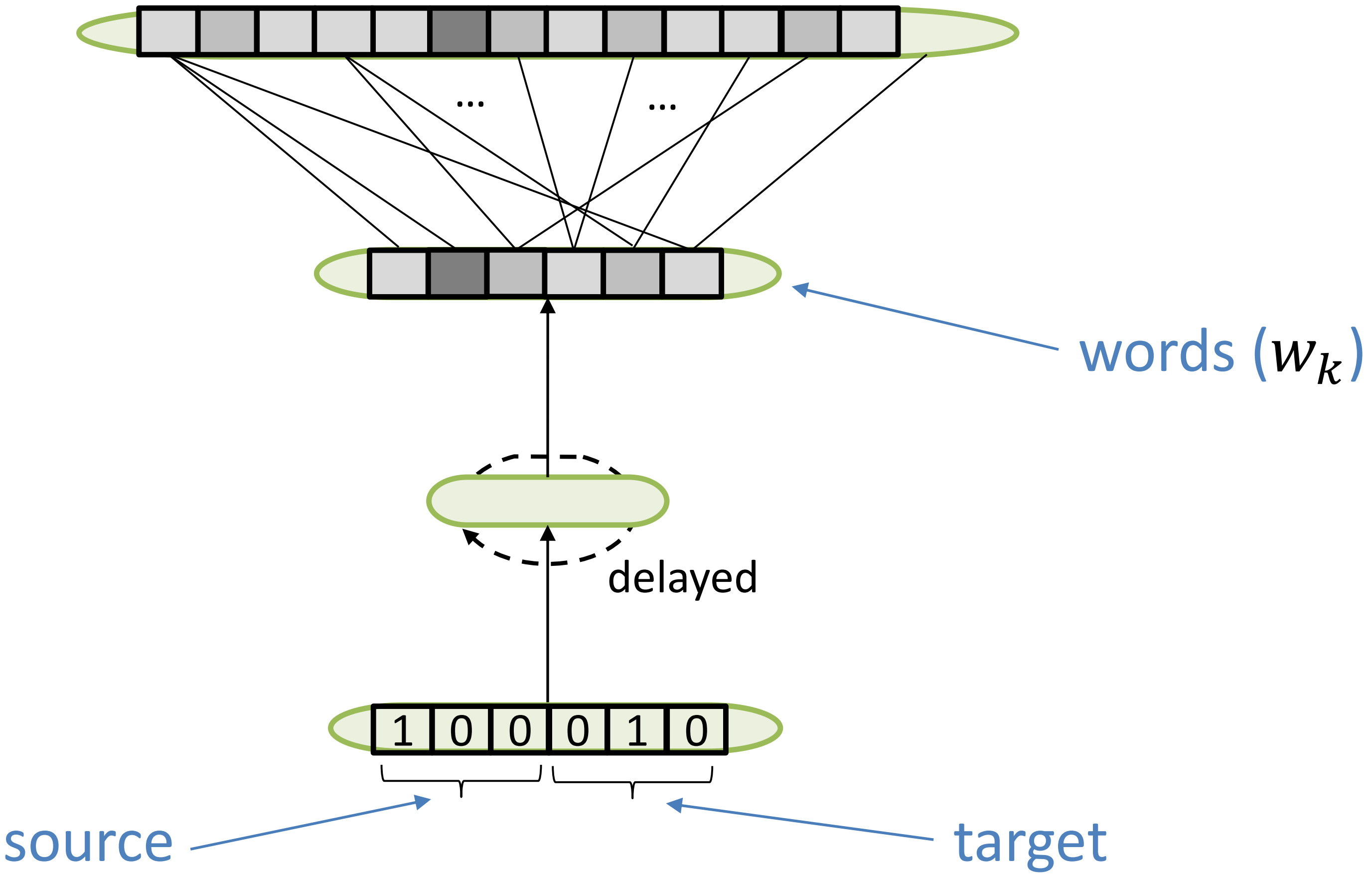

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Model 2: Bag of Words MTU

Add MTU output layer

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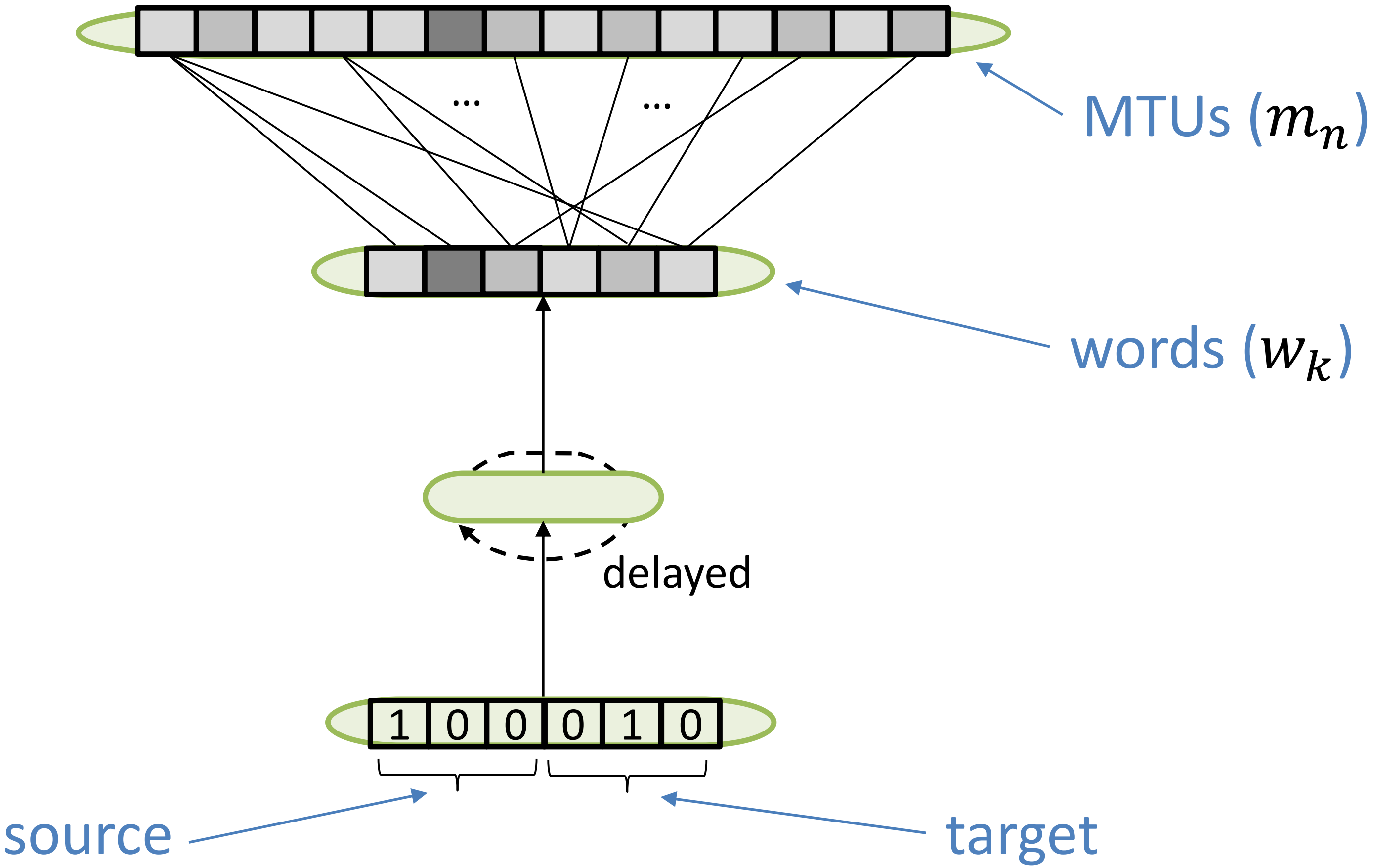

Model 2: Bag of Words MTU

Sparse Mapping MTUs - words

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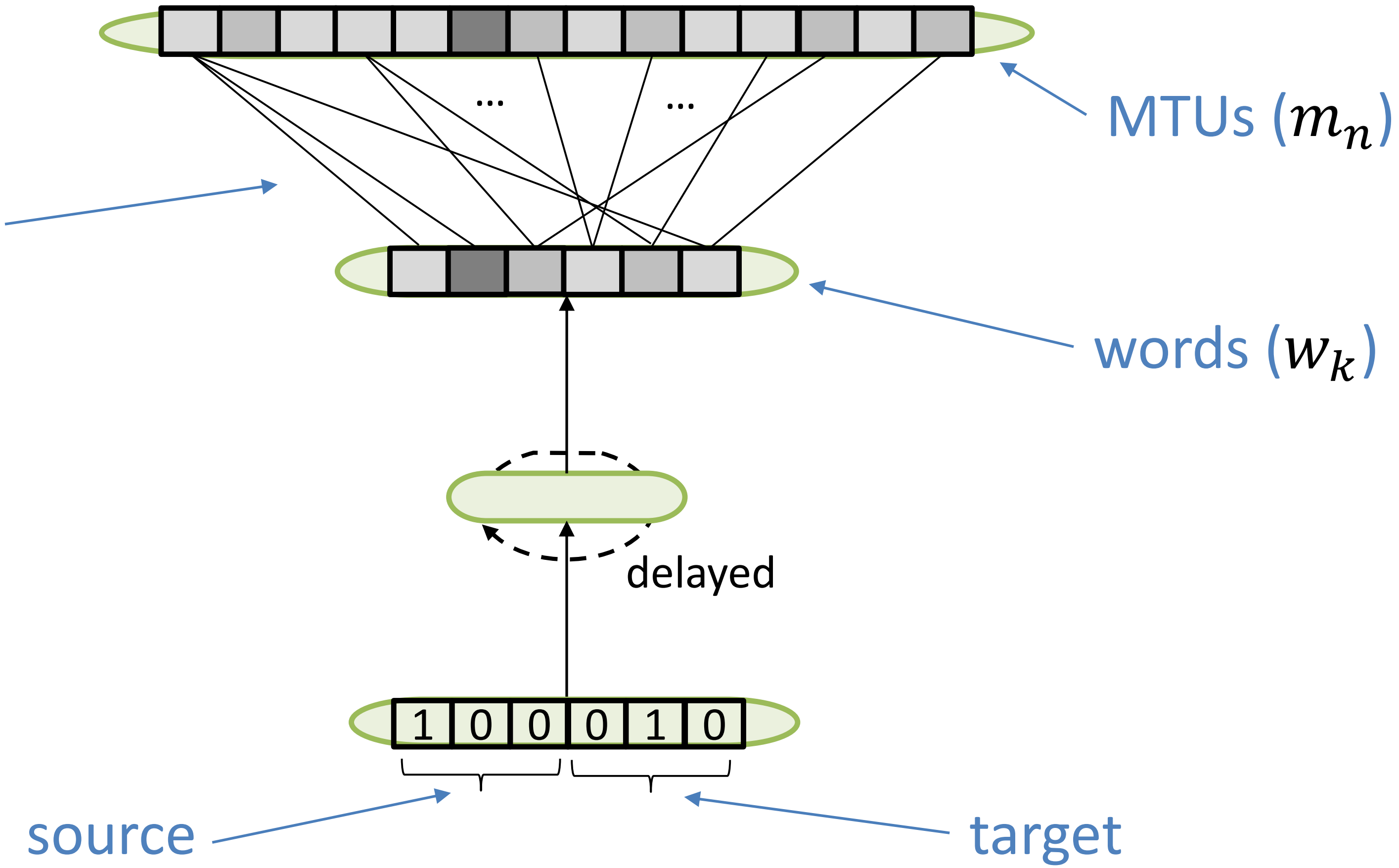
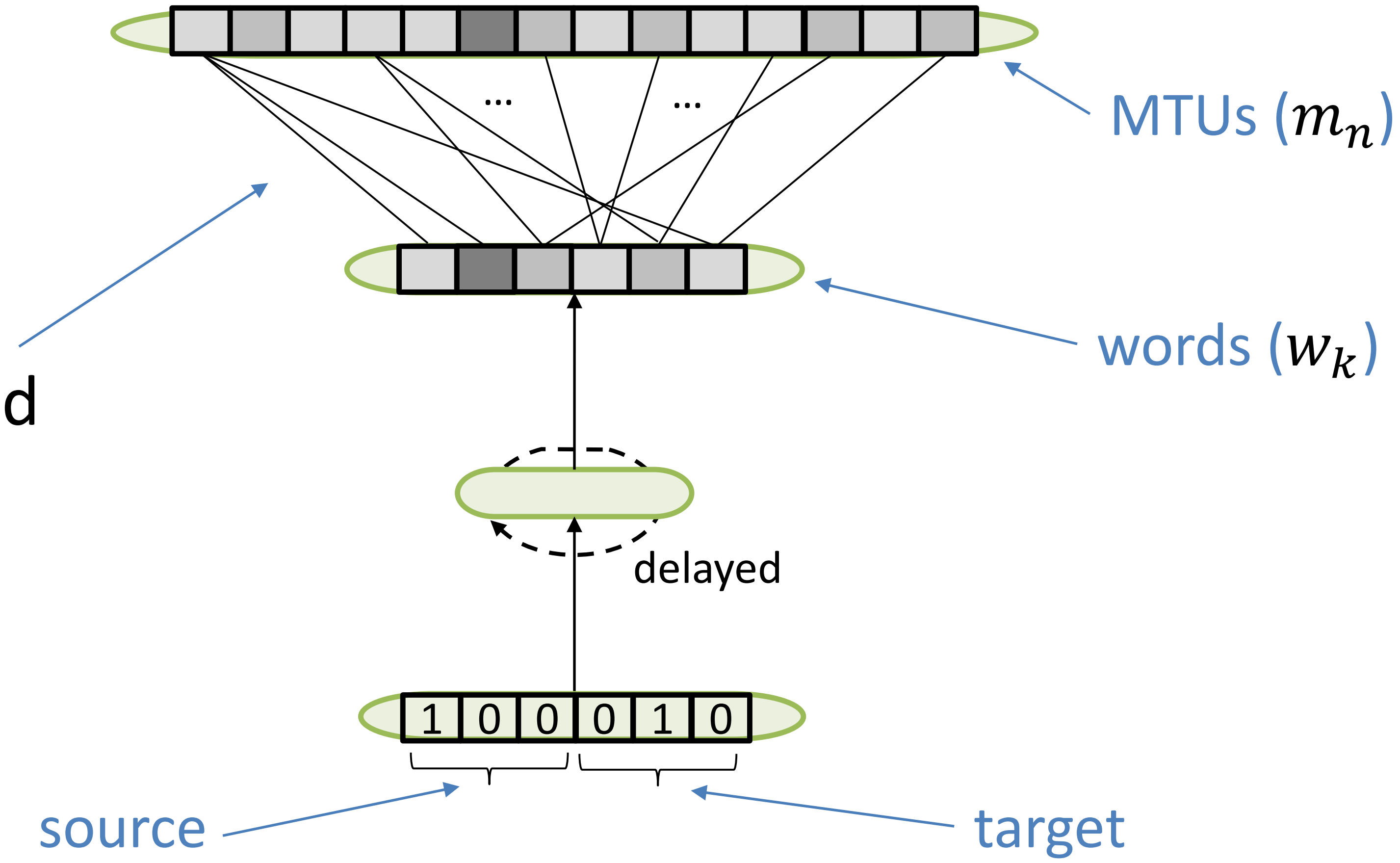
bag of words

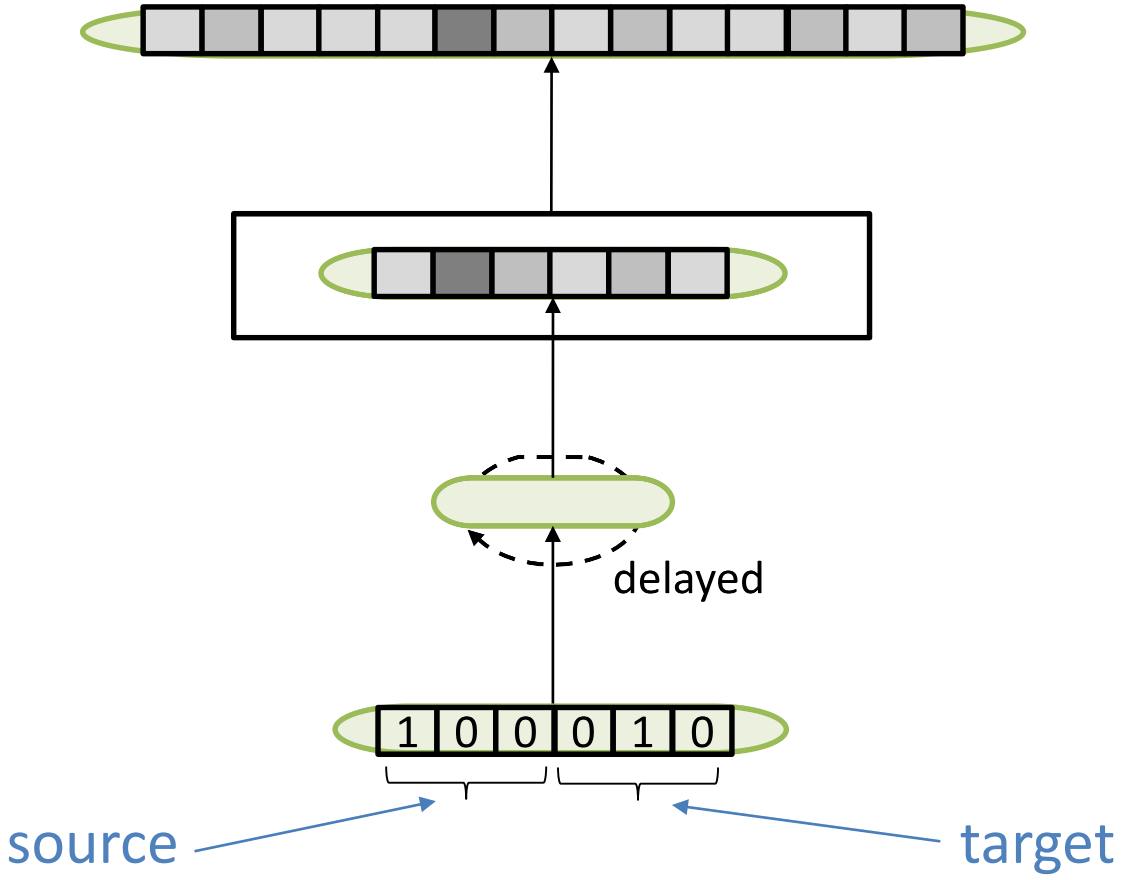


Model 2: Bag of Words MTU

Sparse mapping very imbalanced



Model 2: Simplified Bag of Words MTU



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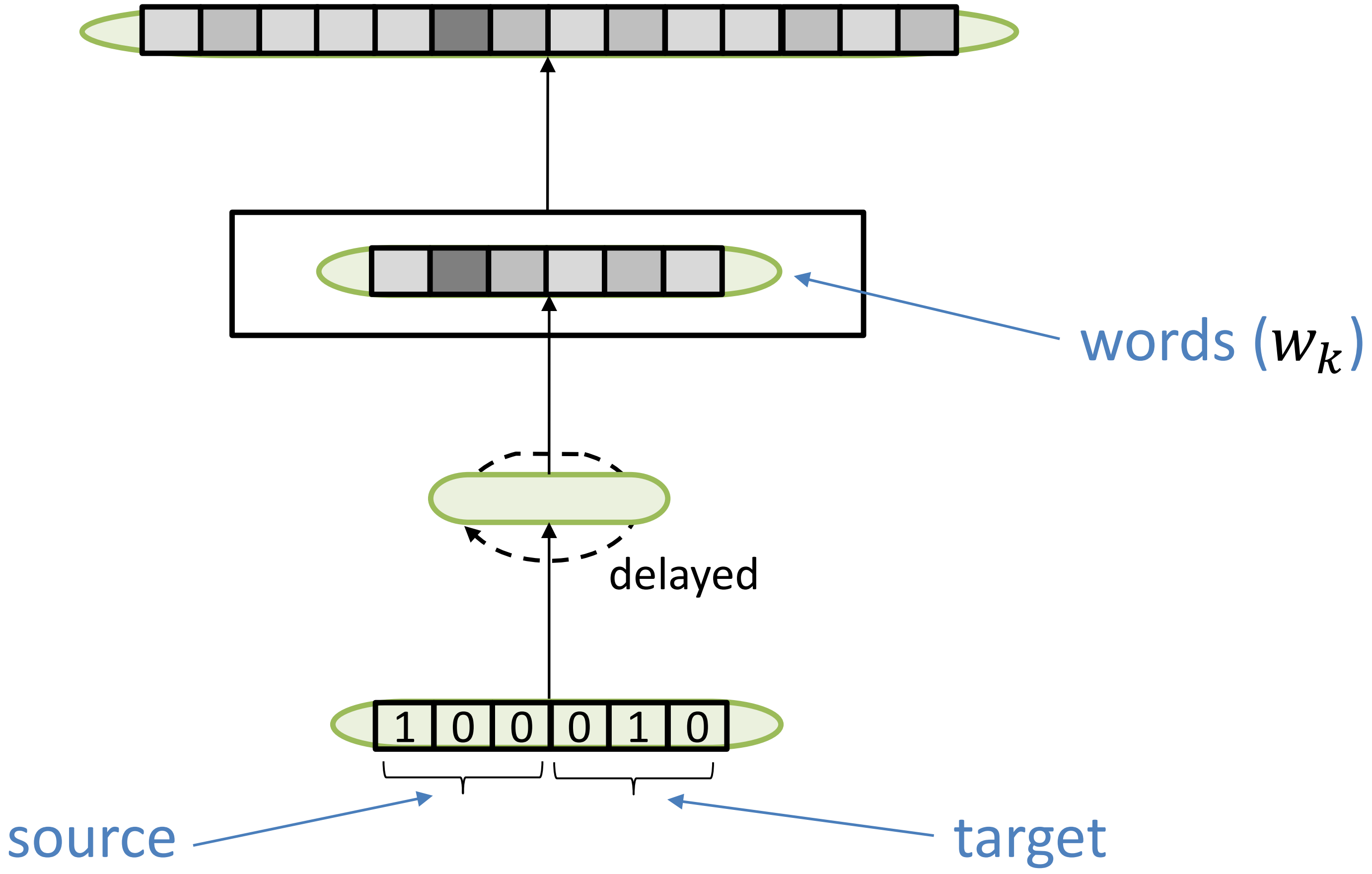

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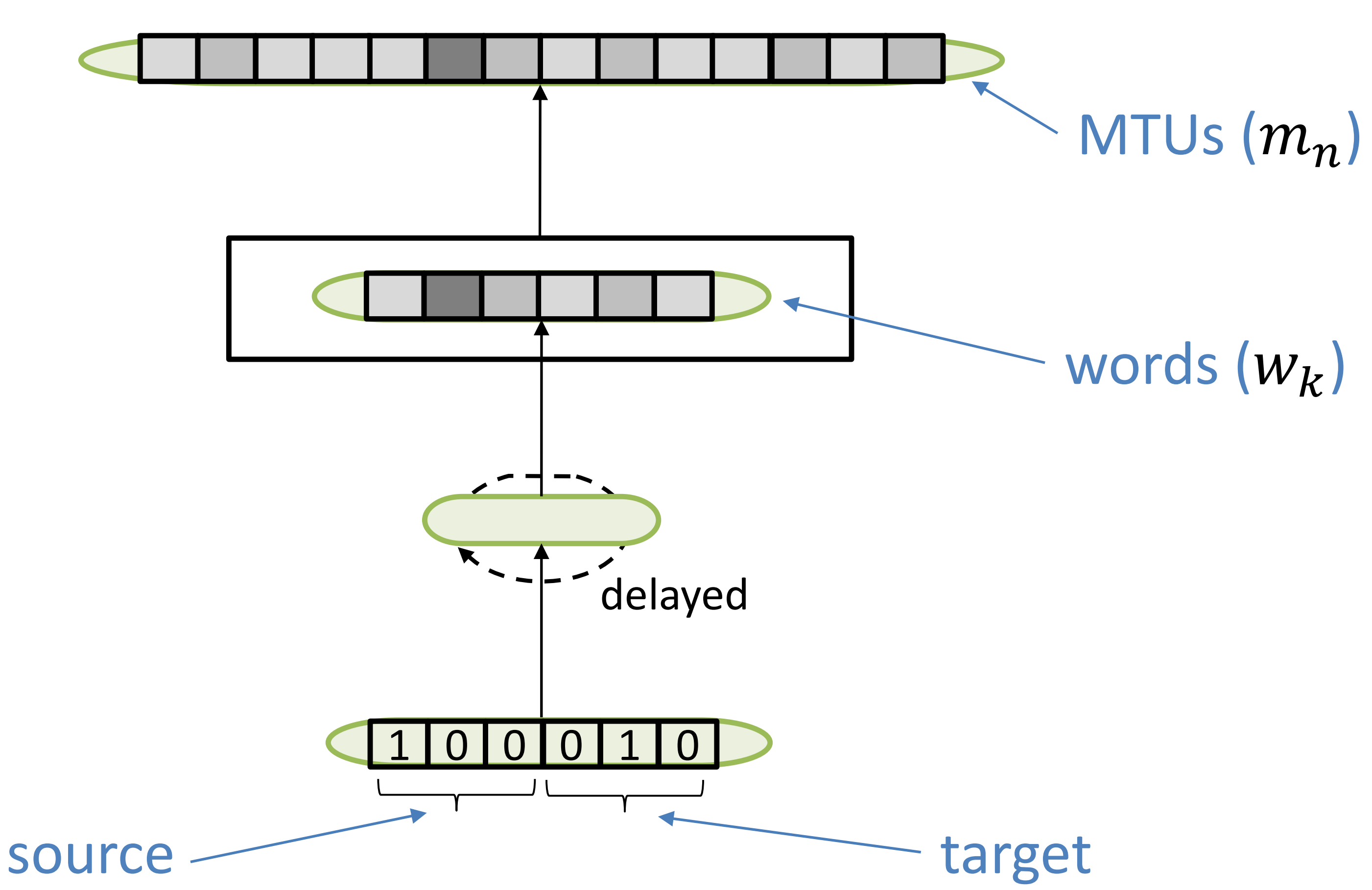
$$p(m_n|h) = \prod_{w \in m_n} p(w|h)$$



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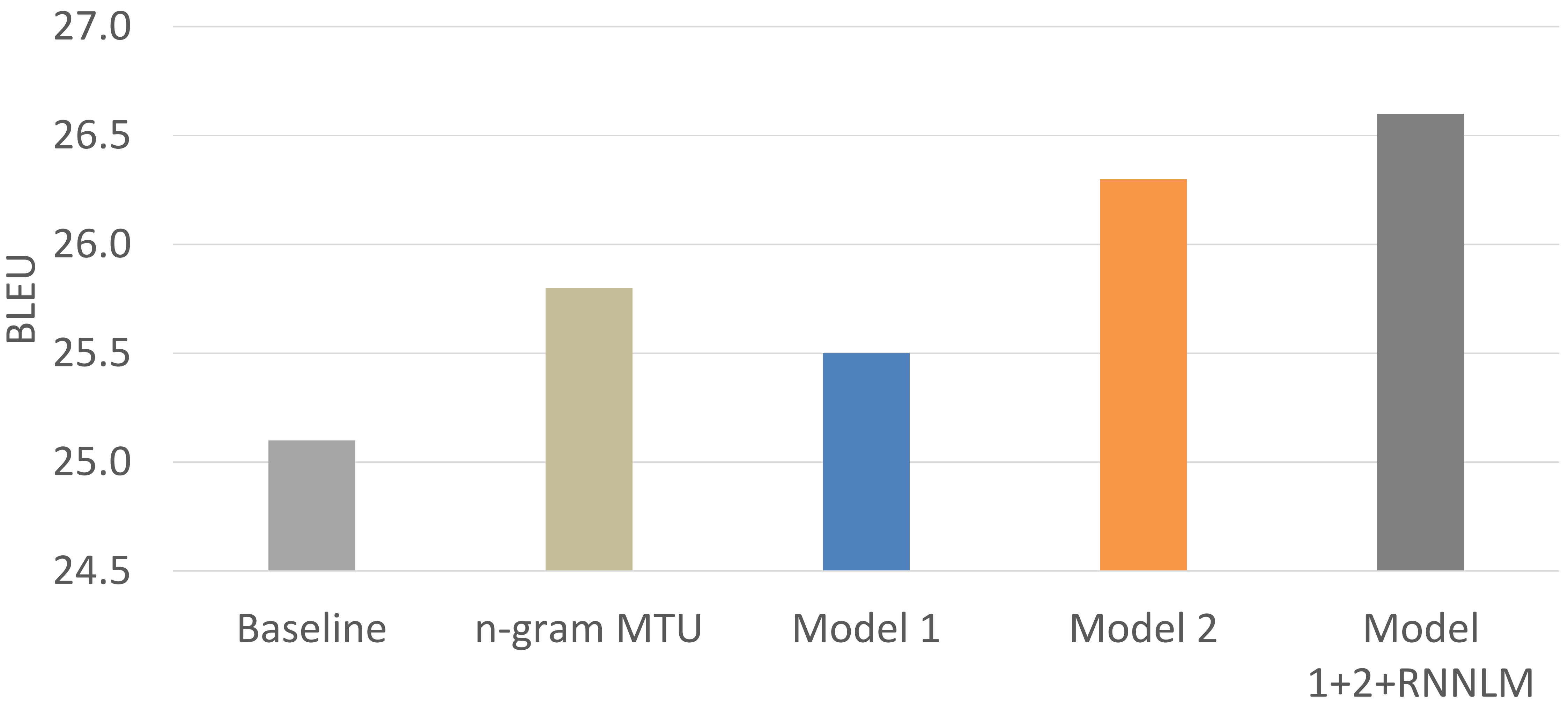
Results

Results


27.0
26.5
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BLEU
Baseline
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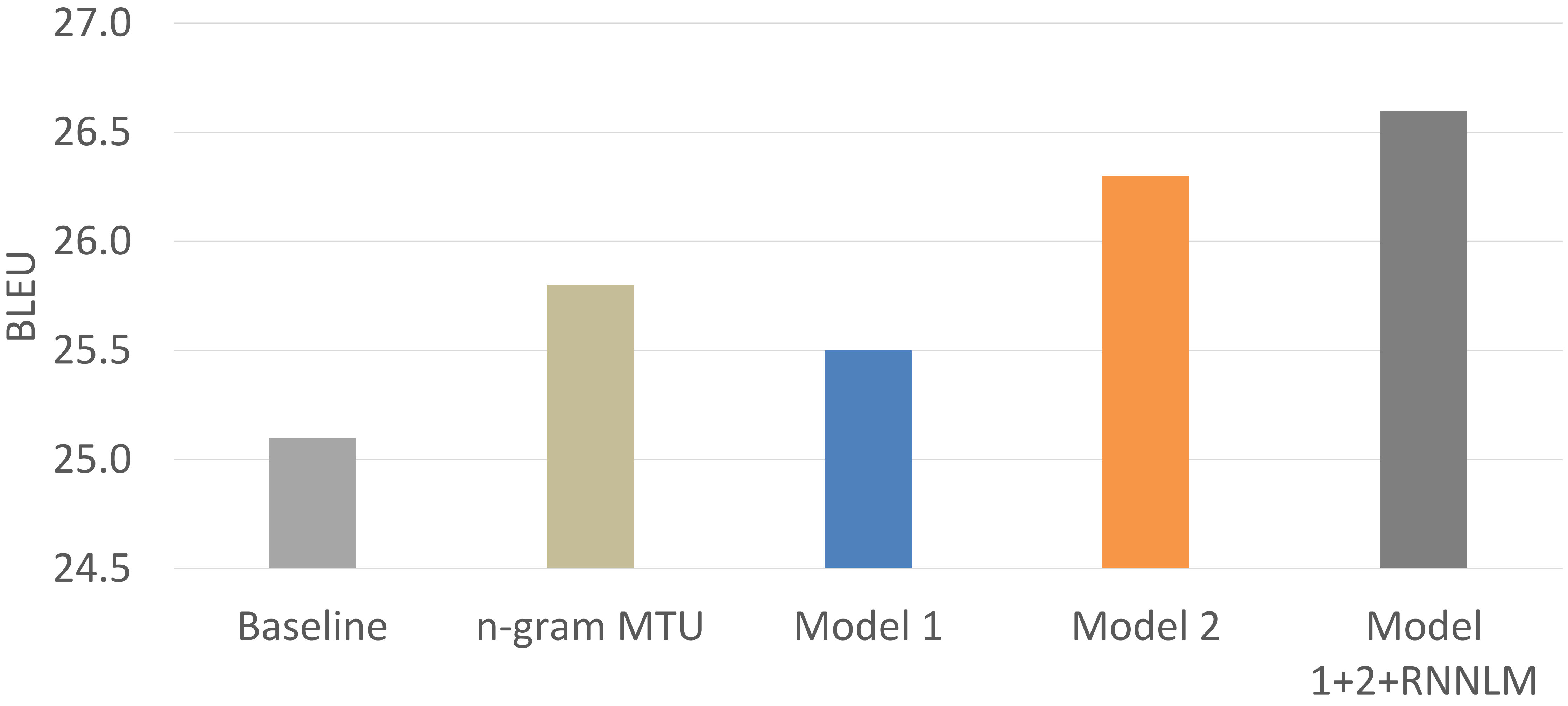
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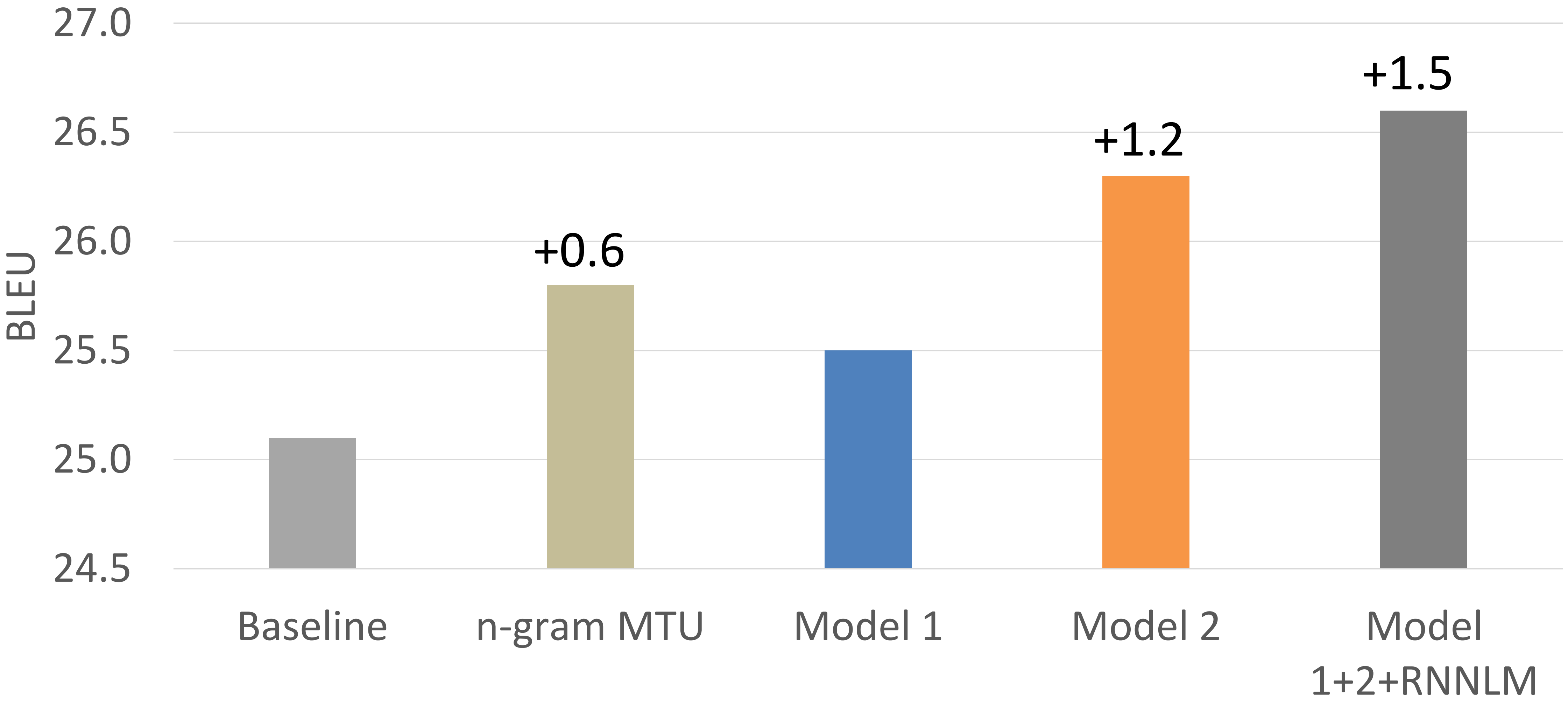
27.0
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BLEU
+0.6
+1.2
+1.5
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n-gram MTU
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Summary so far

- Recurrent net translation models improve phrase-based models (+1.4 BLEU)
- Word-window approach superior to simple sentence representations
- Recurrent MTU models need to be carefully factored
- Bag-of-words factorization adds up to +1.5 BLEU

Overview

- Recurrent neural network joint models (Auli et al., EMNLP 2013)
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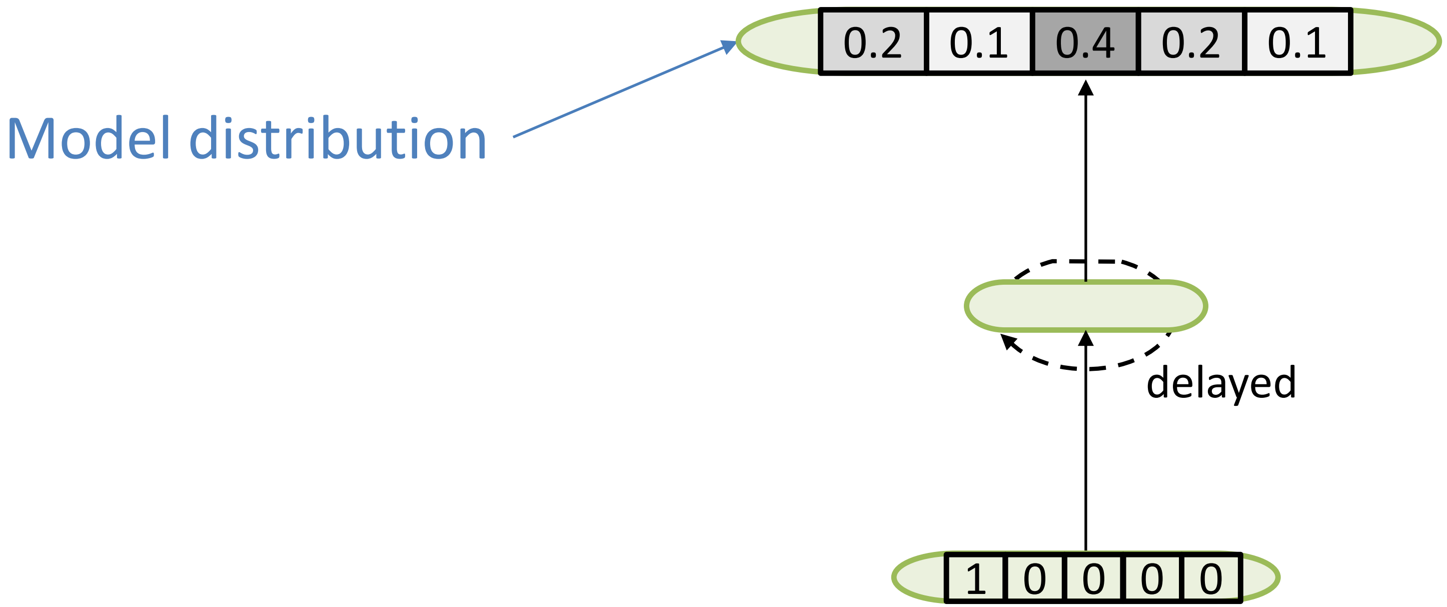
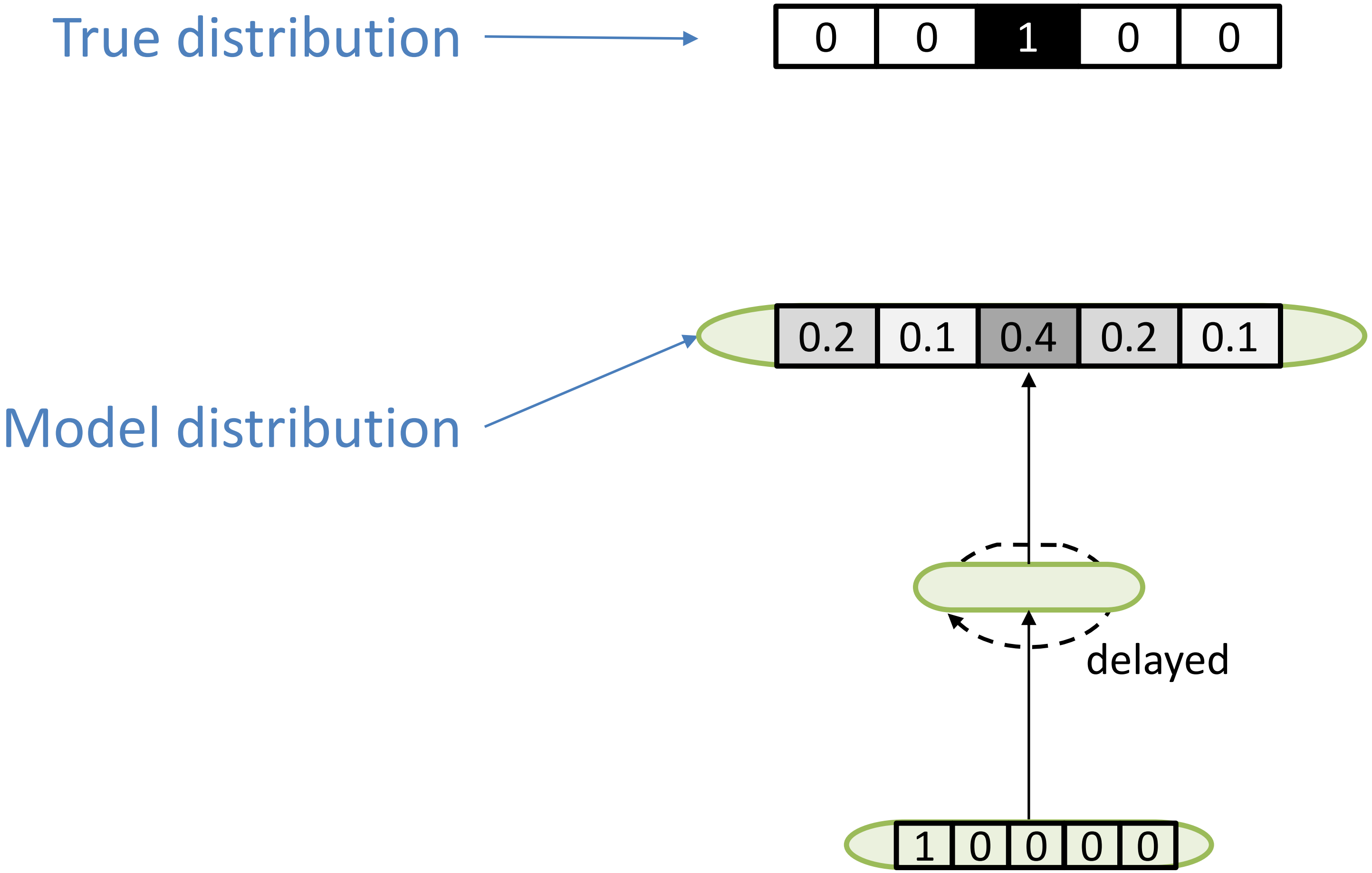
Back propagation with the Cross Entropy Error



$$\max_{\phi} \sum_{i} p(e_i; \phi)$$

Goal: Make reference most likely

Back propagation with the Cross Entropy Error



True distribution

Model distribution

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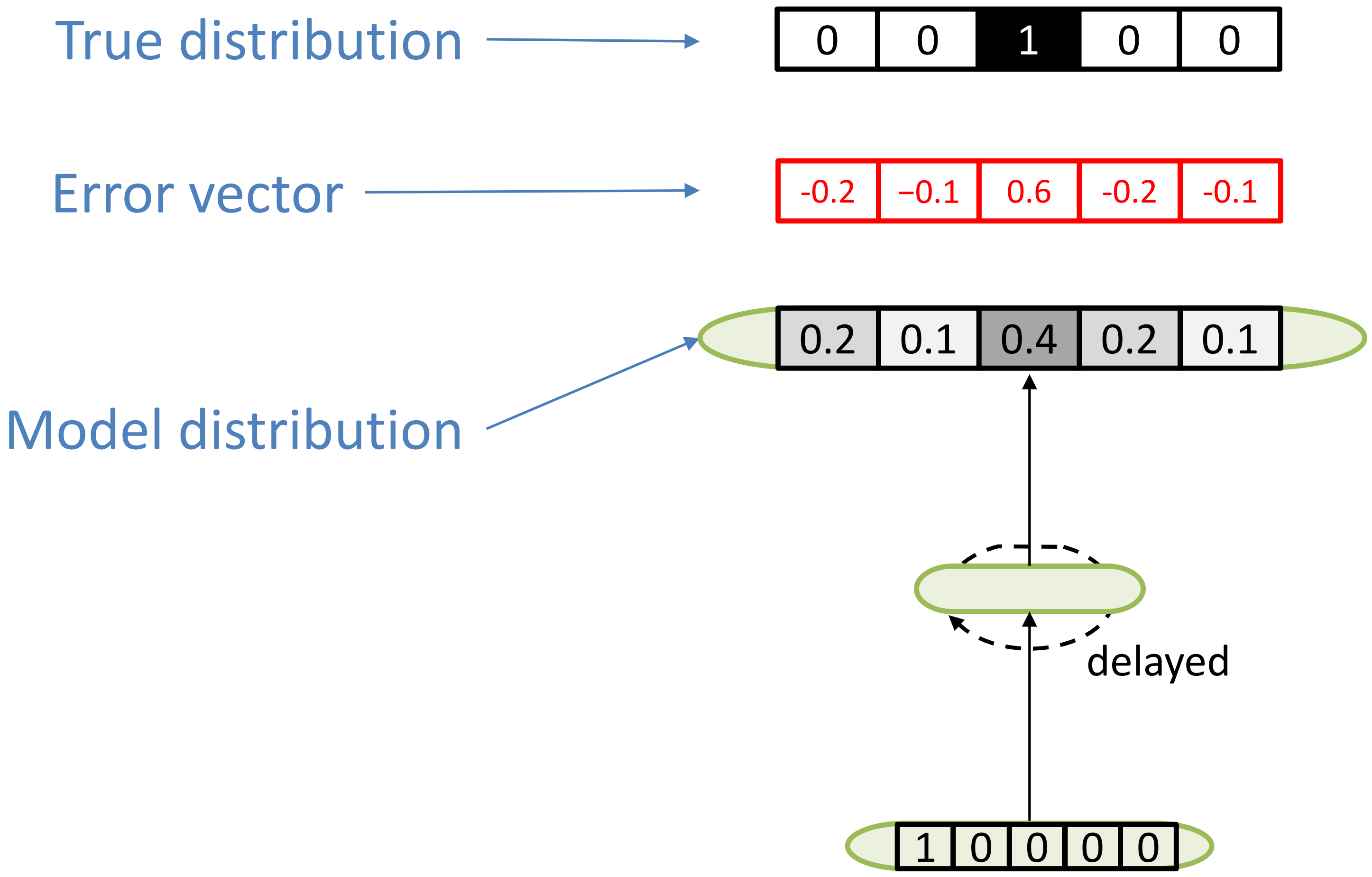

True distribution

0	0	1	0	0

Error vector

-0.2	–0.1	0.6	-0.2	-0.1

Model distribution

0.2	0.1	0.4	0.2	0.1

delayed

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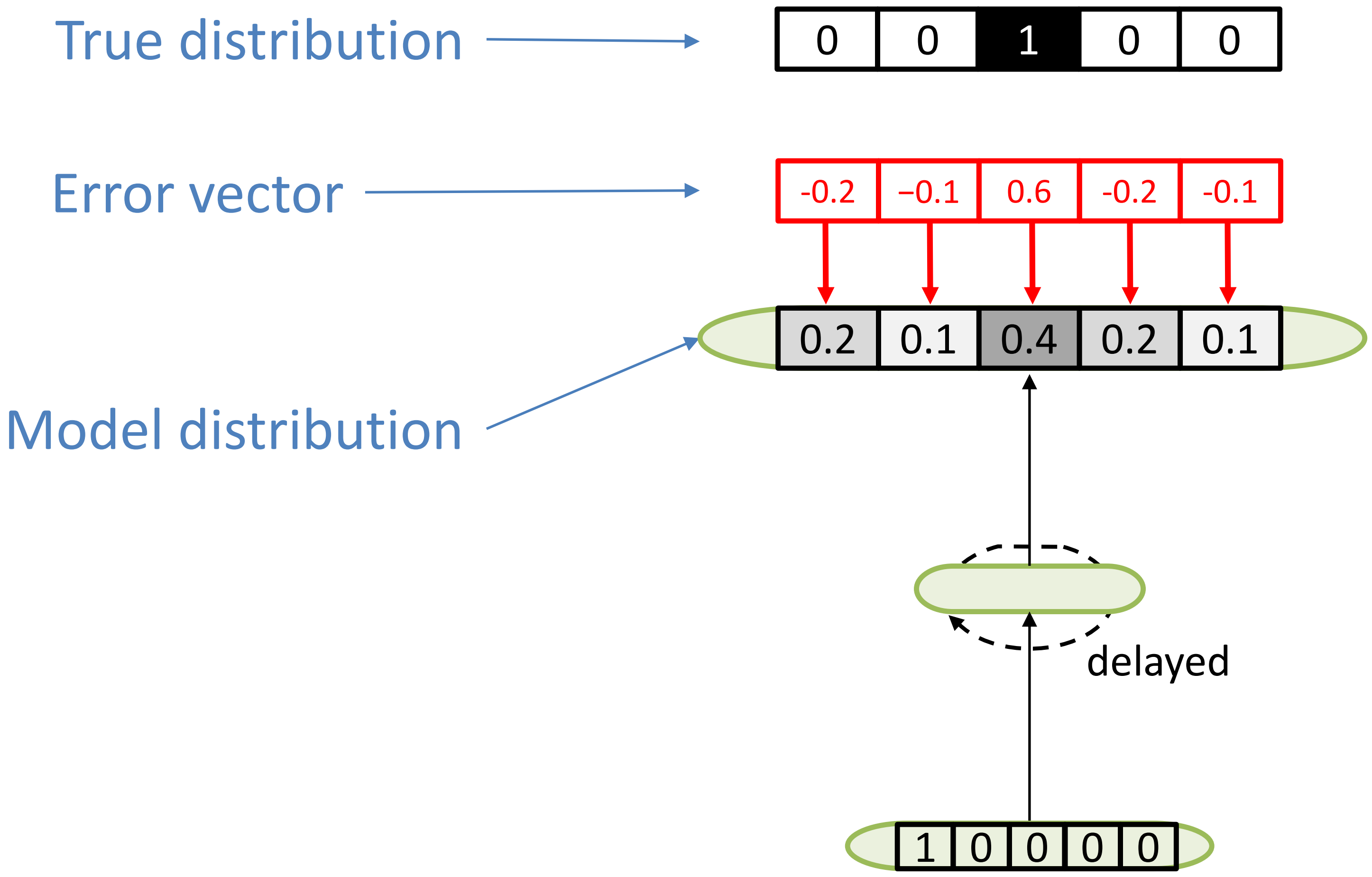

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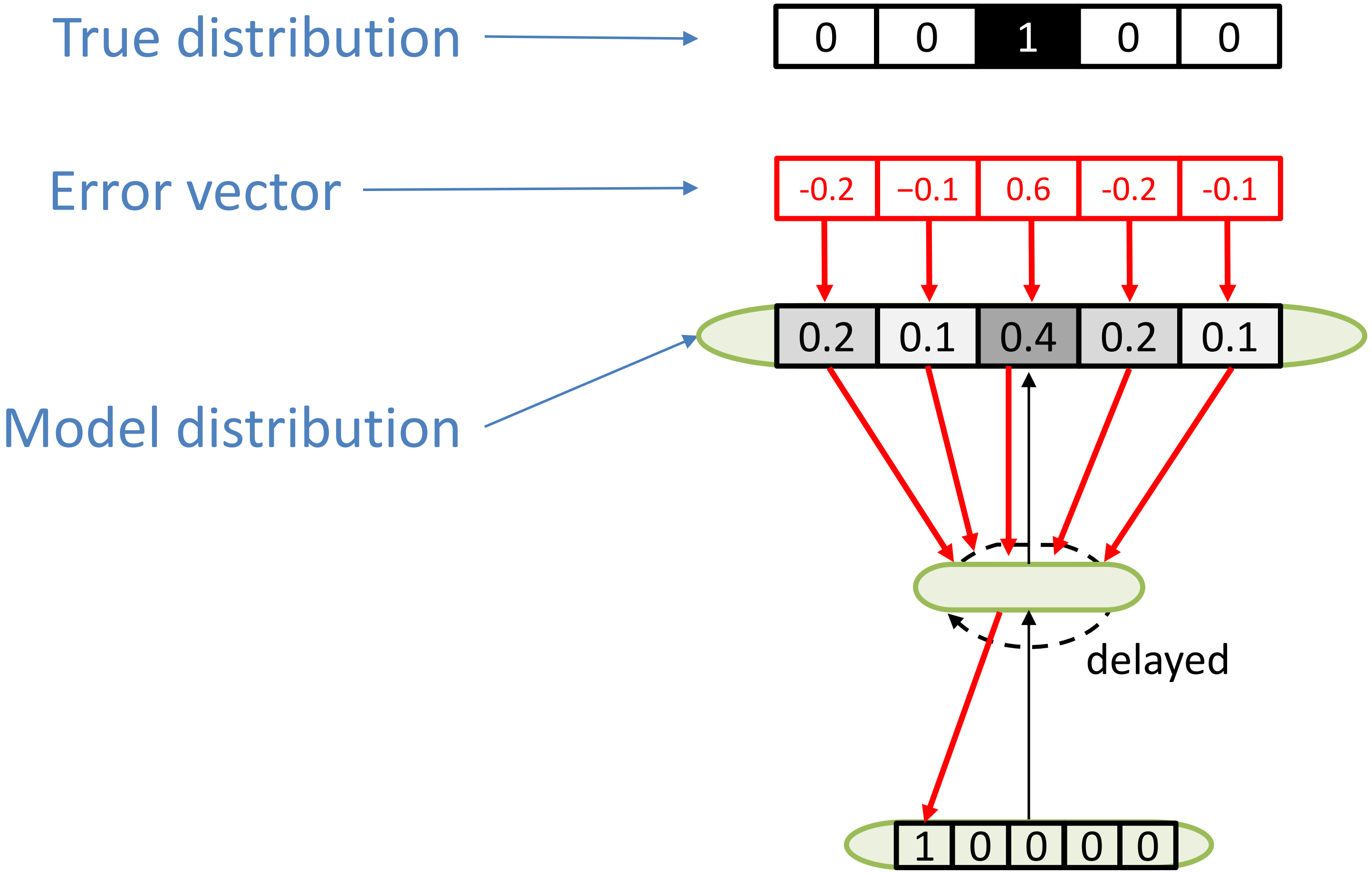

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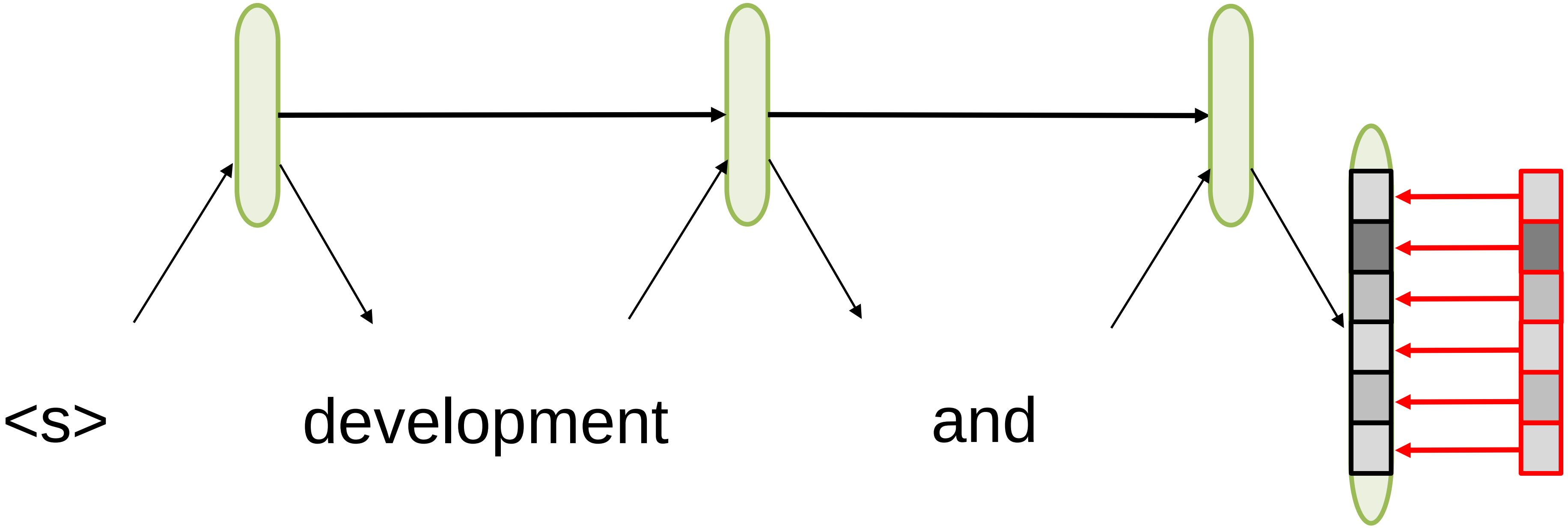

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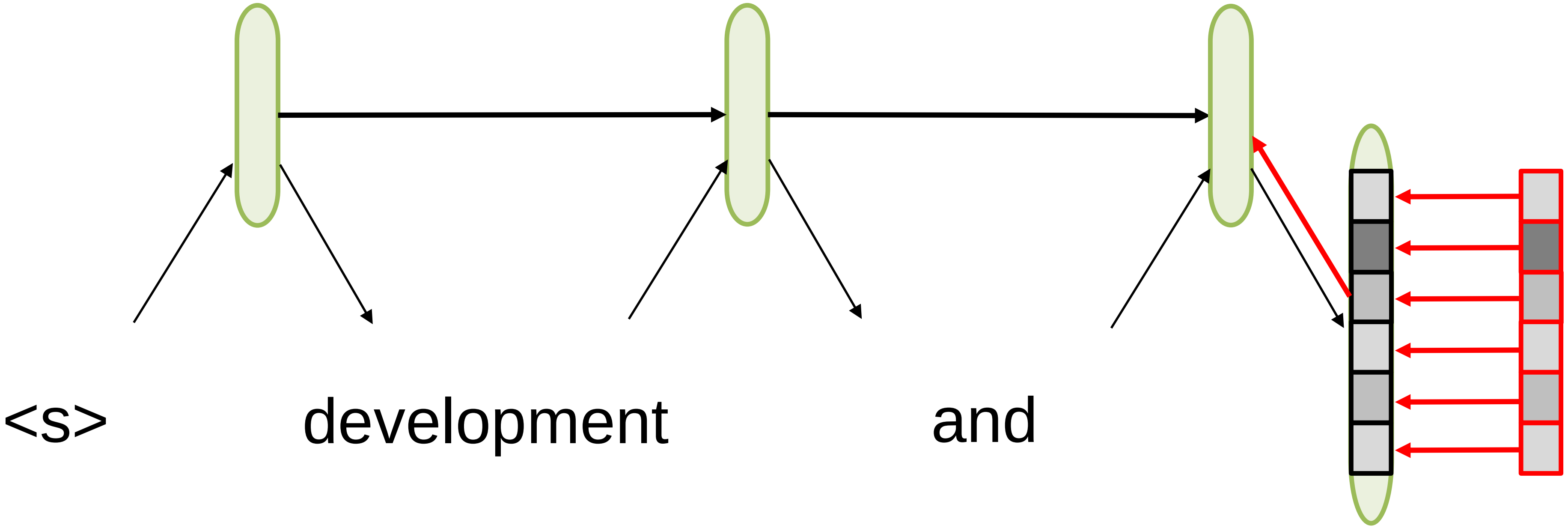

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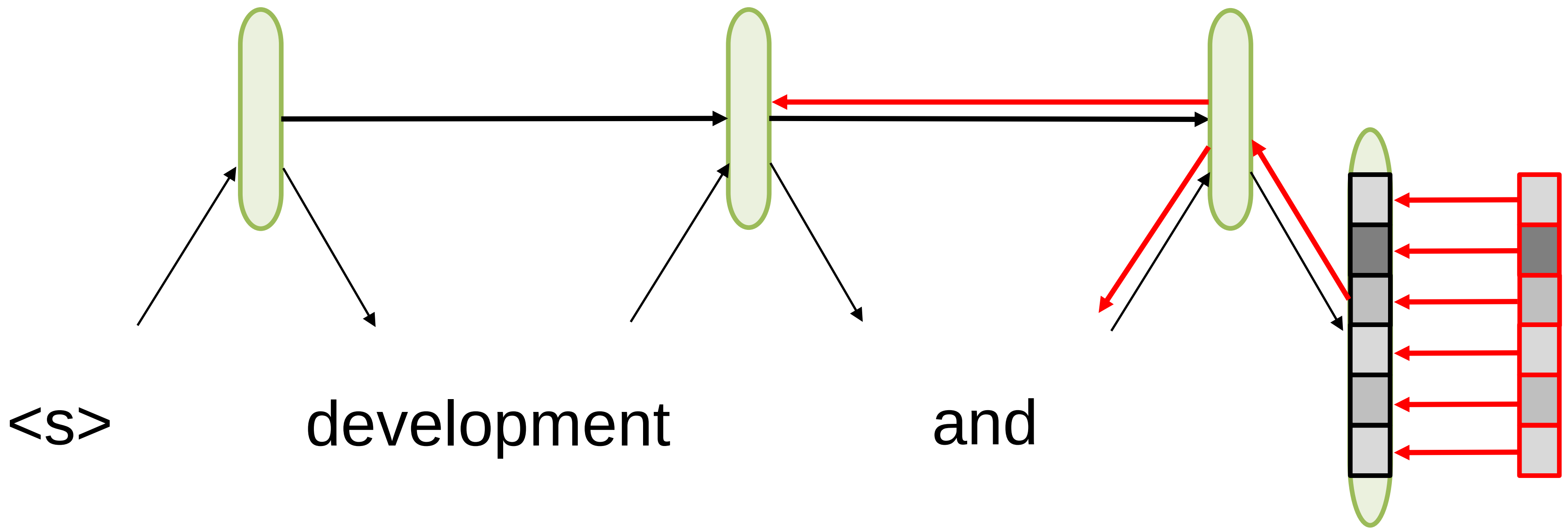

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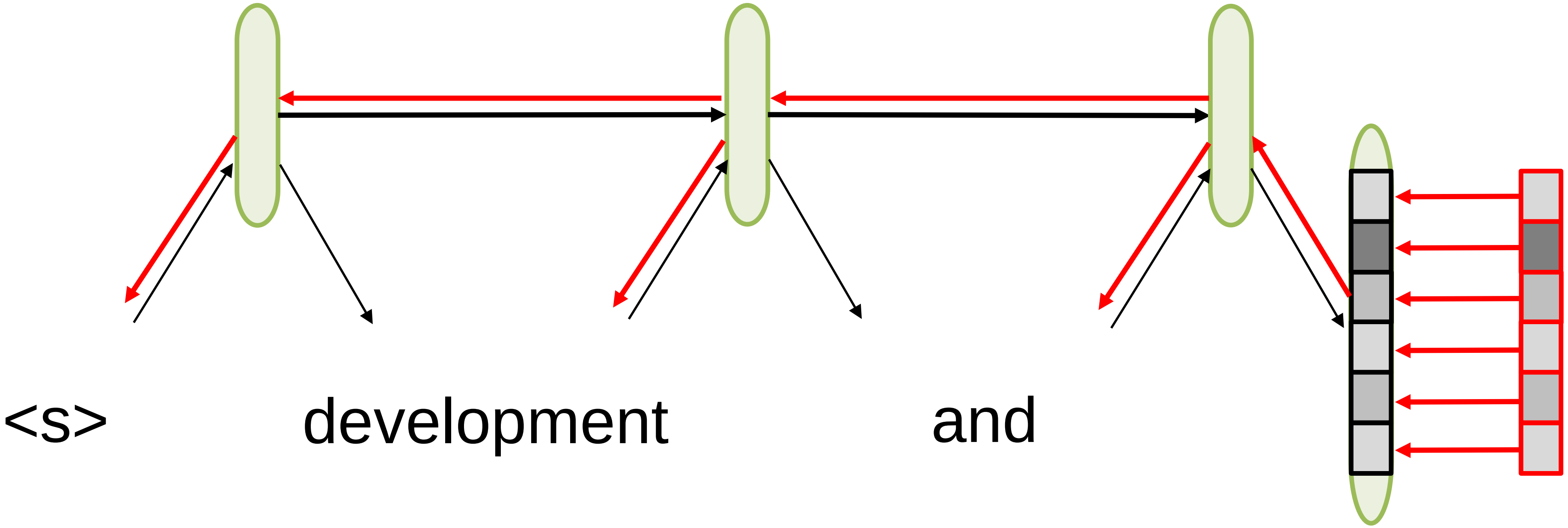

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Task-specific Optimization

- Likelihood training very common
- Optimizing for evaluation metrics difficult, but empirically successful (Och 2003, Smith 2006, Chiang 2009, Gimpel 2010, Hopkins 2011)

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- **Next:** Task-specific training of neural nets for translation

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(Bilingual Evaluation Understudy; Papineni 2002)

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Expected BLEU Training

(Smith 2006, He 2012, Gao 2014)

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Desired translation output

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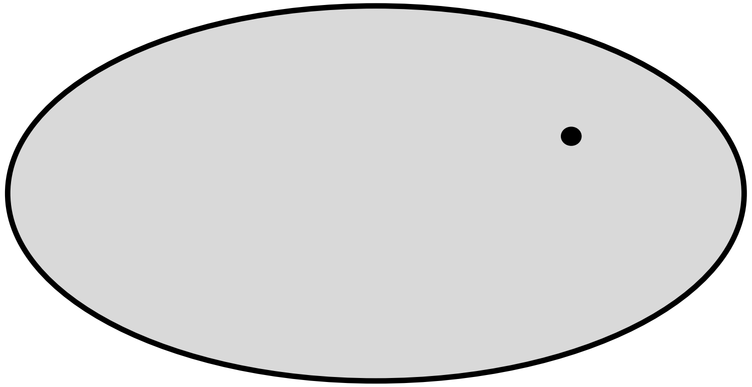

xBLEU: $$\max_{\phi} \sum_{i} \sum_{e \in E(f_i)} \mathrm{sBLEU}(e,e_i)\, p(e|f_i;\phi)$$

Expected BLEU Training

(Smith 2006, He 2012, Gao 2014)

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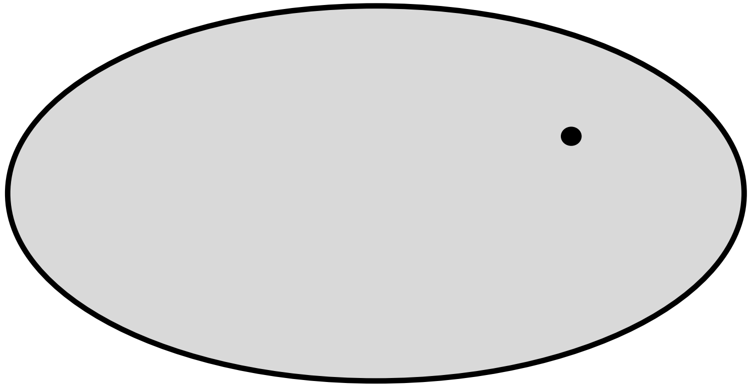
L: $$\max_{\phi} \sum_{i} p(e_i|f_i;\phi)$$



xBLEU: $$\max_{\phi} \sum_{i} \sum_{e\in E(f_i)} \mathrm{sBLEU}(e,e_i)\, p(e|f_i;\phi)$$

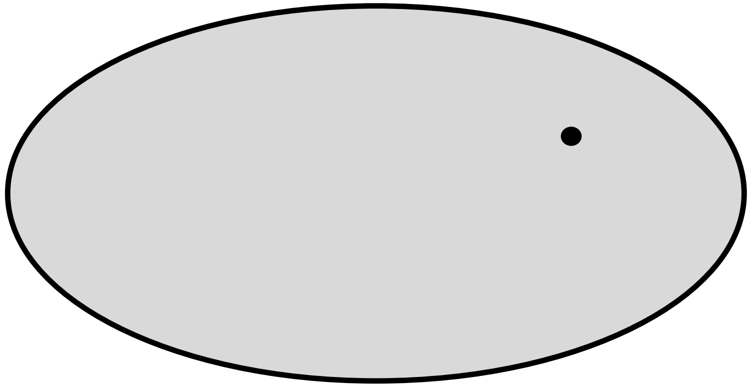
Generated outputs Gain function Human translation

Expected BLEU Training

(Smith 2006, He 2012, Gao 2014)

Desired translation output

L: $$\max_{\phi} \sum_{i} p(e_i | f_i; \phi)$$



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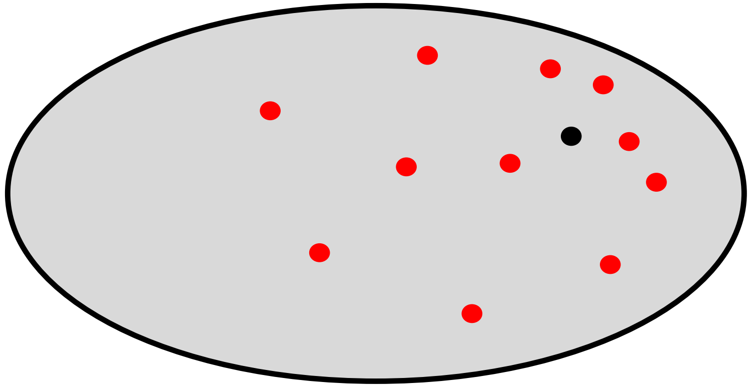
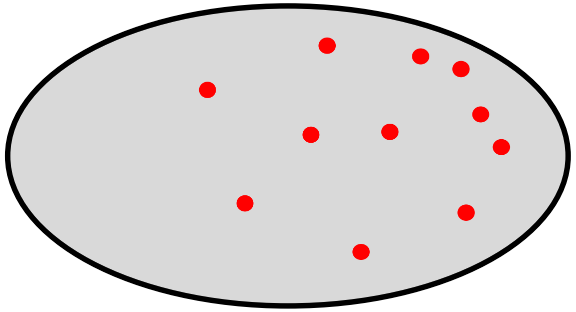


Generated outputs

Gain function

Human translation

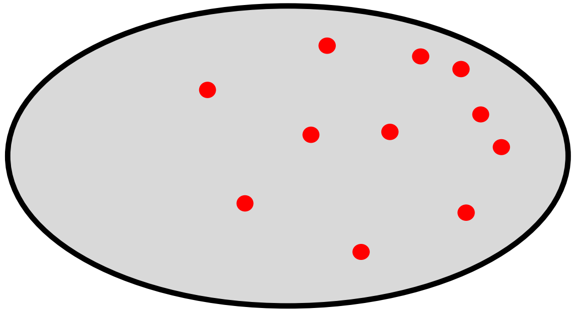
Expected BLEU Training



本 地区 的 发展 和 进步

Human: development and progress of the region

Expected BLEU Training

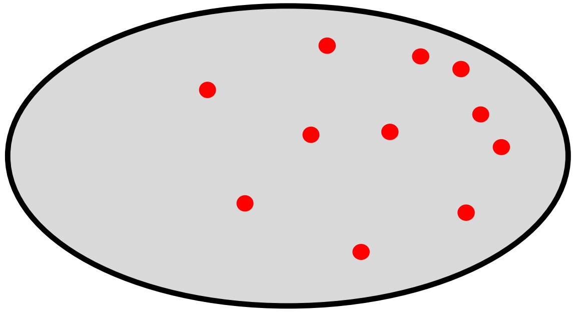


本 地区 的 发展 和 进步

Human: development and progress of the region

advance and progress of the region
development and progress of this province
progress of this region

Expected BLEU Training

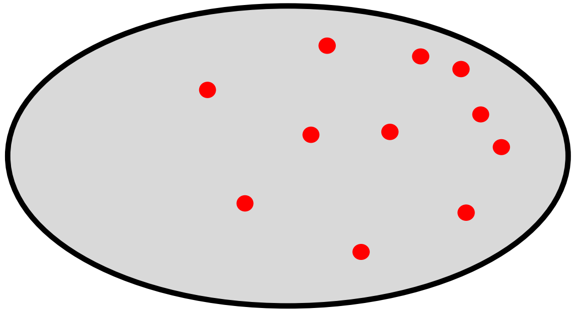


本 地区 的 发展 和 进步

Human: development and progress of the region

	sBLEU
advance and progress of the region	0.8
development and progress of this province	0.5
progress of this region	0.3

Expected BLEU Training

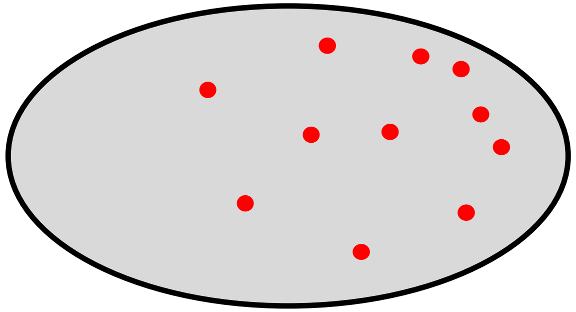


本 地区 的 发展 和 进步

Human: development and progress of the region

	sBLEU	$p_t(e\|f_i)$
advance and progress of the region	0.8	0.2
development and progress of this province	0.5	0.3
progress of this region	0.3	0.5

Expected BLEU Training



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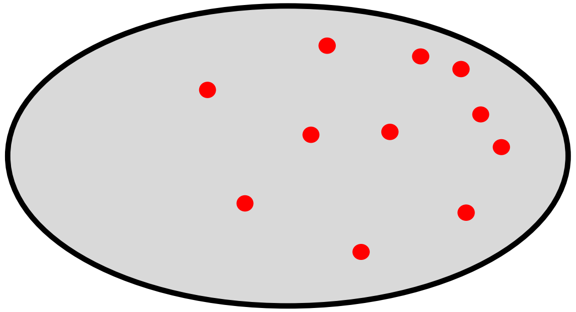

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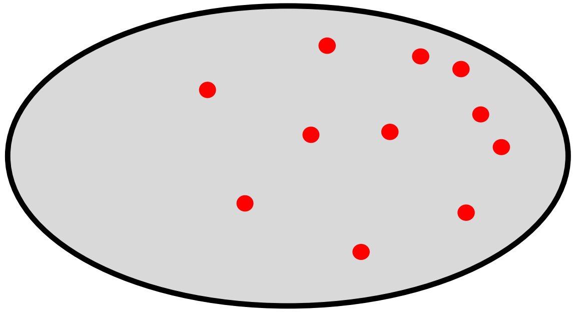

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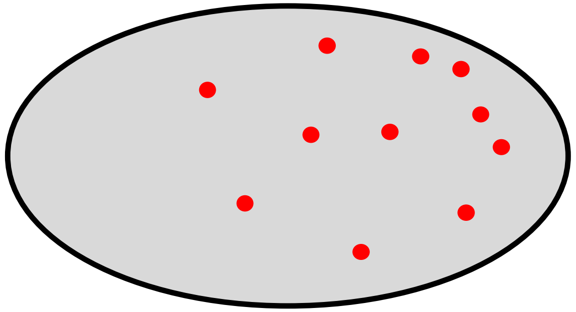
$$\text{xBLEU} = \sum_{i} \sum_{e \in E(f_i)} \text{sBLEU}(e, e_i)\, p(e|f_i) \; = \; 0.5$$

Expected BLEU Training



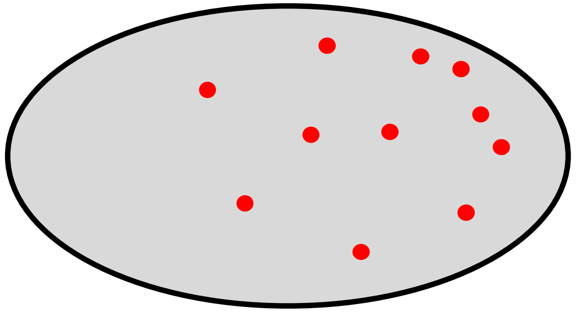
本 地区 的 发展 和 进步

Human: development and progress of the region

	sBLEU	$p_t(e\|f_i)$	δ_t
advance and progress of the region	0.8	0.2	0.3
development and progress of this province	0.5	0.3	0
progress of this region	0.3	0.5	-0.2

$$\text{xBLEU} = \sum_{i} \sum_{e \in E(f_i)} \text{sBLEU}(e, e_i)\, p(e|f_i) = \boxed{0.5}$$

Expected BLEU Training



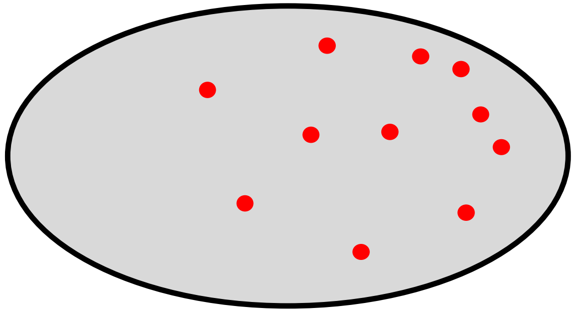
本 地区 的 发展 和 进步

Human: development and progress of the region

	sBLEU	$p_t(e\|f_i)$	δ_t	$p_{t+1}(e\|f_i)$
advance and progress of the region	0.8	0.2	0.3	0.5
development and progress of this province	0.5	0.3	0	0.3
progress of this region	0.3	0.5	-0.2	0.1

$$\text{xBLEU} = \sum_{i} \sum_{e \in E(f_i)} \text{sBLEU}(e, e_i)\, p(e|f_i) \;=\; 0.5$$

Expected BLEU Training



本 地区 的 发展 和 进步

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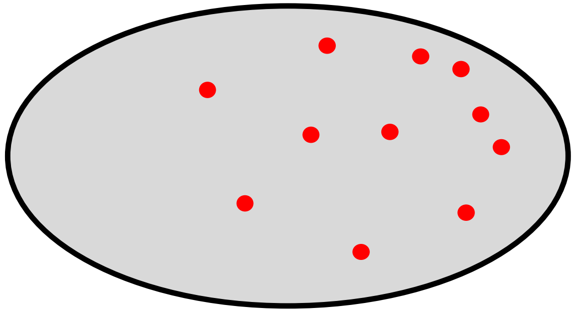
Expected BLEU Training



本 地区 的 发展 和 进步

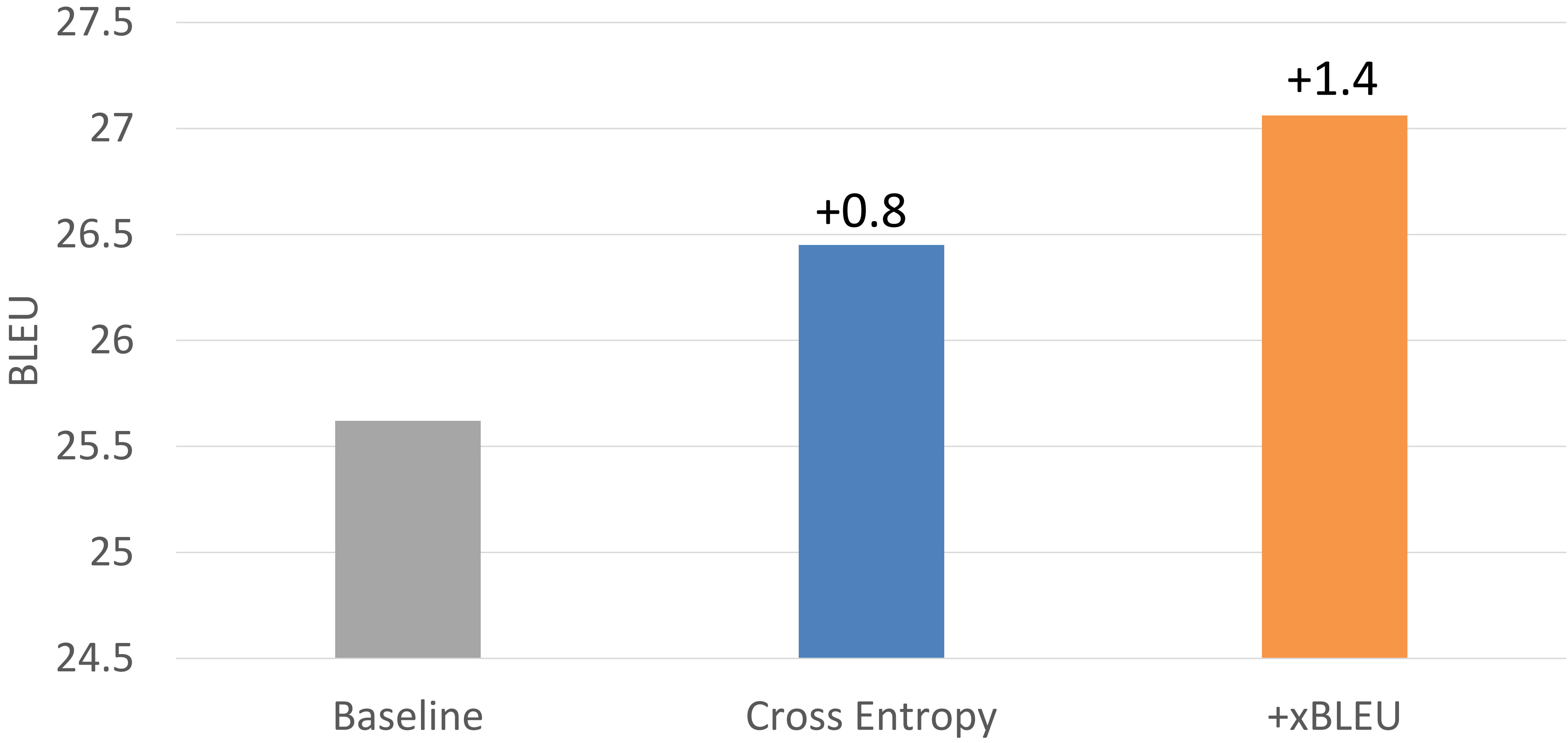
Human: development and progress of the region

	sBLEU	$p_t(e\|f_i)$	δ_t	$p_{t+1}(e\|f_i)$
advance and progress of the region	0.8	0.2	0.3	0.5
development and progress of this province	0.5	0.3	0	0.3
progress of this region	0.3	0.5	-0.2	0.1

$$\mathrm{xBLEU} = \sum_{i} \sum_{e \in E(f_i)} \mathrm{sBLEU}(e, e_i)\, p(e|f_i) = 0.5 \rightarrow \boxed{\mathbf{0.6}}$$

Results

Results


BLEU
27.5
27
26.5
26
25.5
25
24.5
+0.8
+1.4
Baseline
Cross Entropy
+xBLEU

Overview

- Recurrent neural network joint models (EMNLP 2013)
  Combined language and translation modeling

- Minimum translation modeling with recurrent nets (EACL 2014)
  Sequence models over bilingual units

- Training recurrent nets (ACL 2014)
  Expected BLEU training for neural network translation models

- Large-scale discriminative training for SMT (Auli et al., in submission)
  Training millions of linear ordering features with expected BLEU

Large-scale Discriminative Training for SMT

- Tuning: Minimum Error Rate Training: ~30 features (Och, 2003)

Large-scale Discriminative Training for SMT

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Large-scale Discriminative Training for SMT

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- Recent success: MIRA-trained sparse ordering models (Cherry, 2013)

Large-scale Discriminative Training for SMT

- Tuning: Minimum Error Rate Training: ~30 features (Och, 2003)
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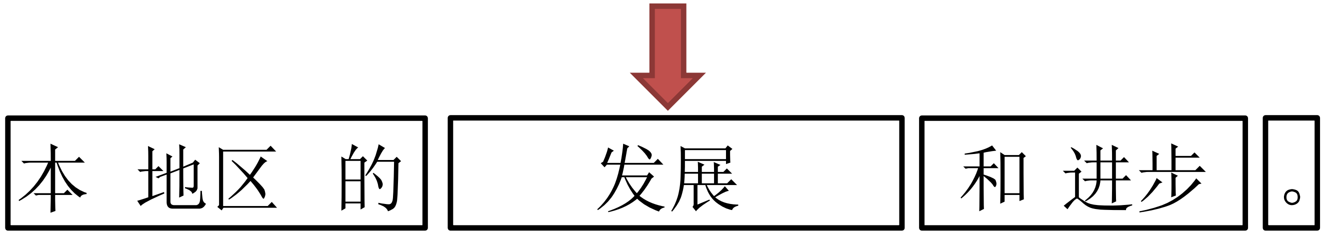
- Several others: PRO (Hopkins, 2011), MIRA (Chiang 2009 Watanabe 2007)
- Recent success: MIRA-trained sparse ordering models (Cherry, 2013)
- **Next:** Training large-scale sparse ordering models with expected BLEU

Lexicalized Reordering

本 地区 的 | 发展 | 和 进步 | 。

Lexicalized Reordering



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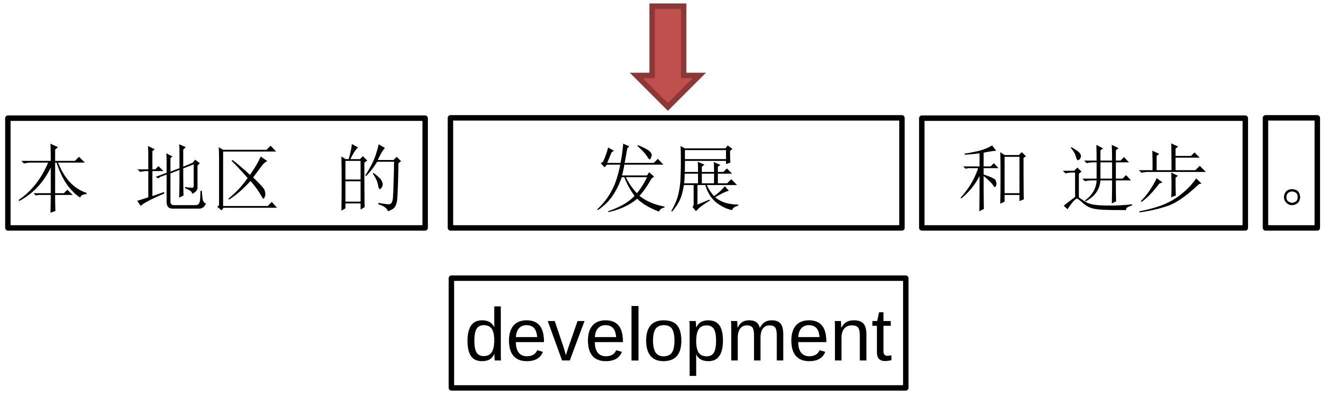
Lexicalized Reordering



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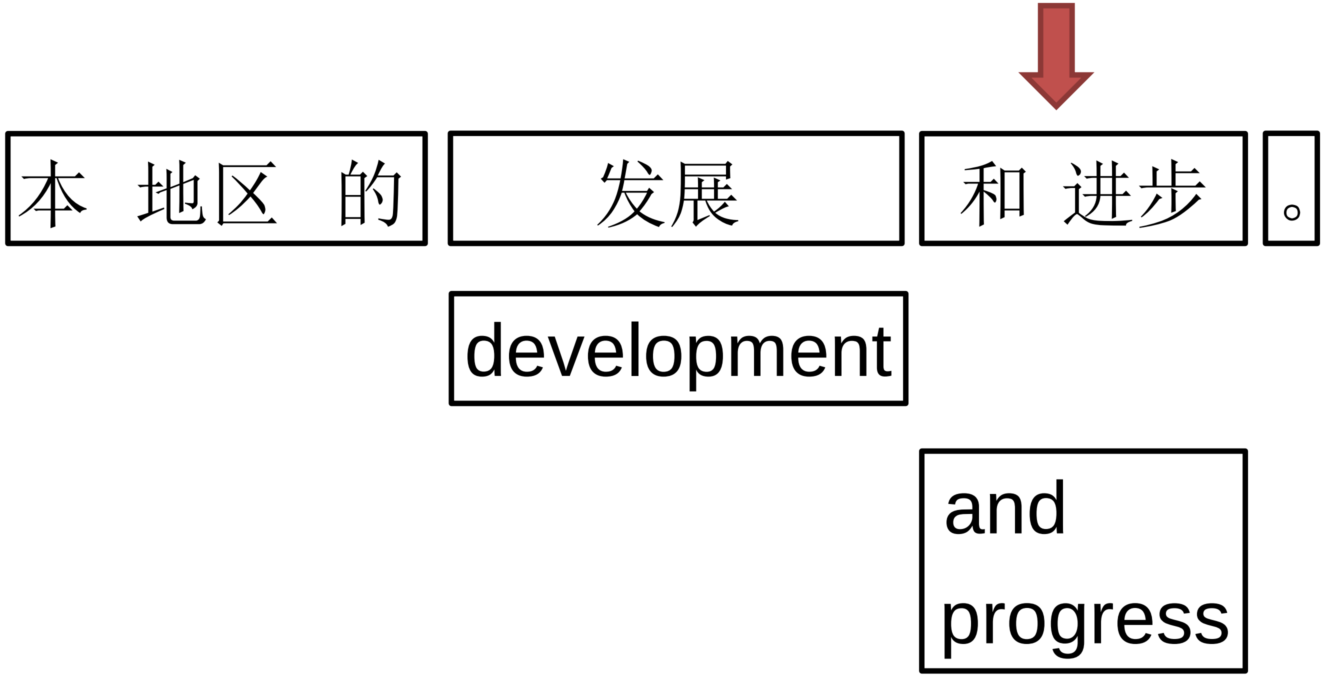
development

Lexicalized Reordering



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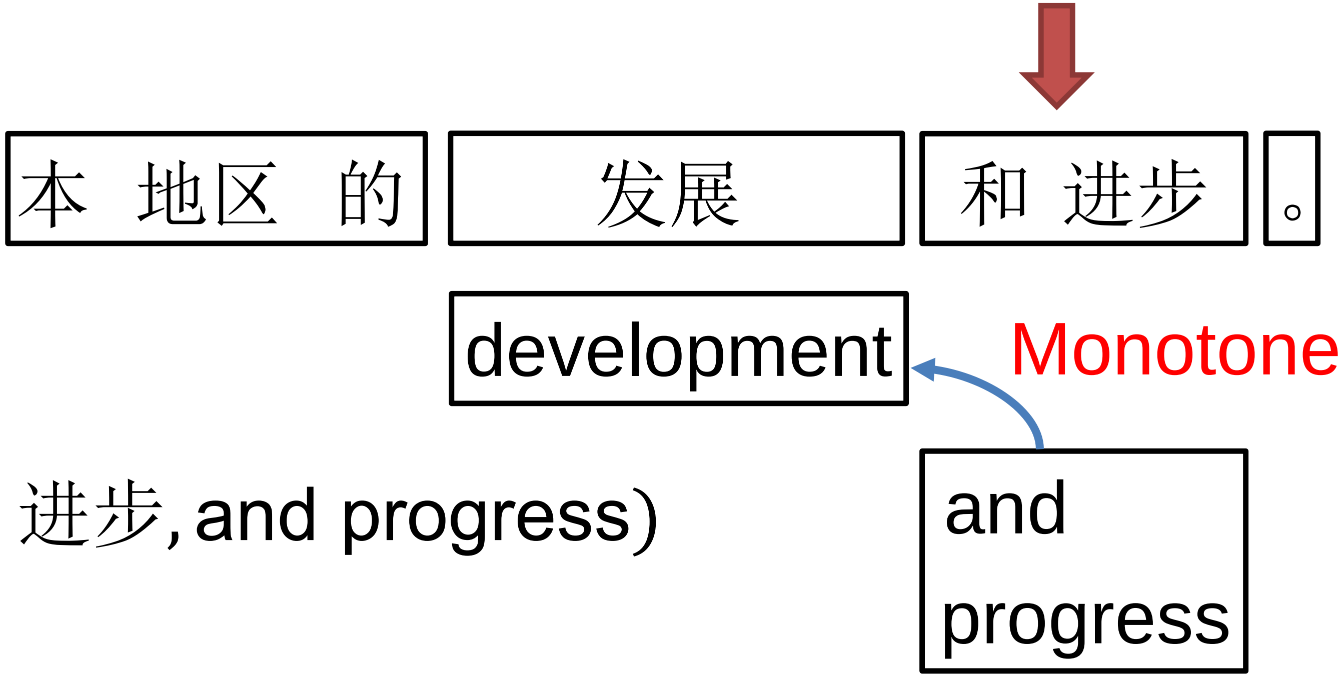
development

and progress

Lexicalized Reordering



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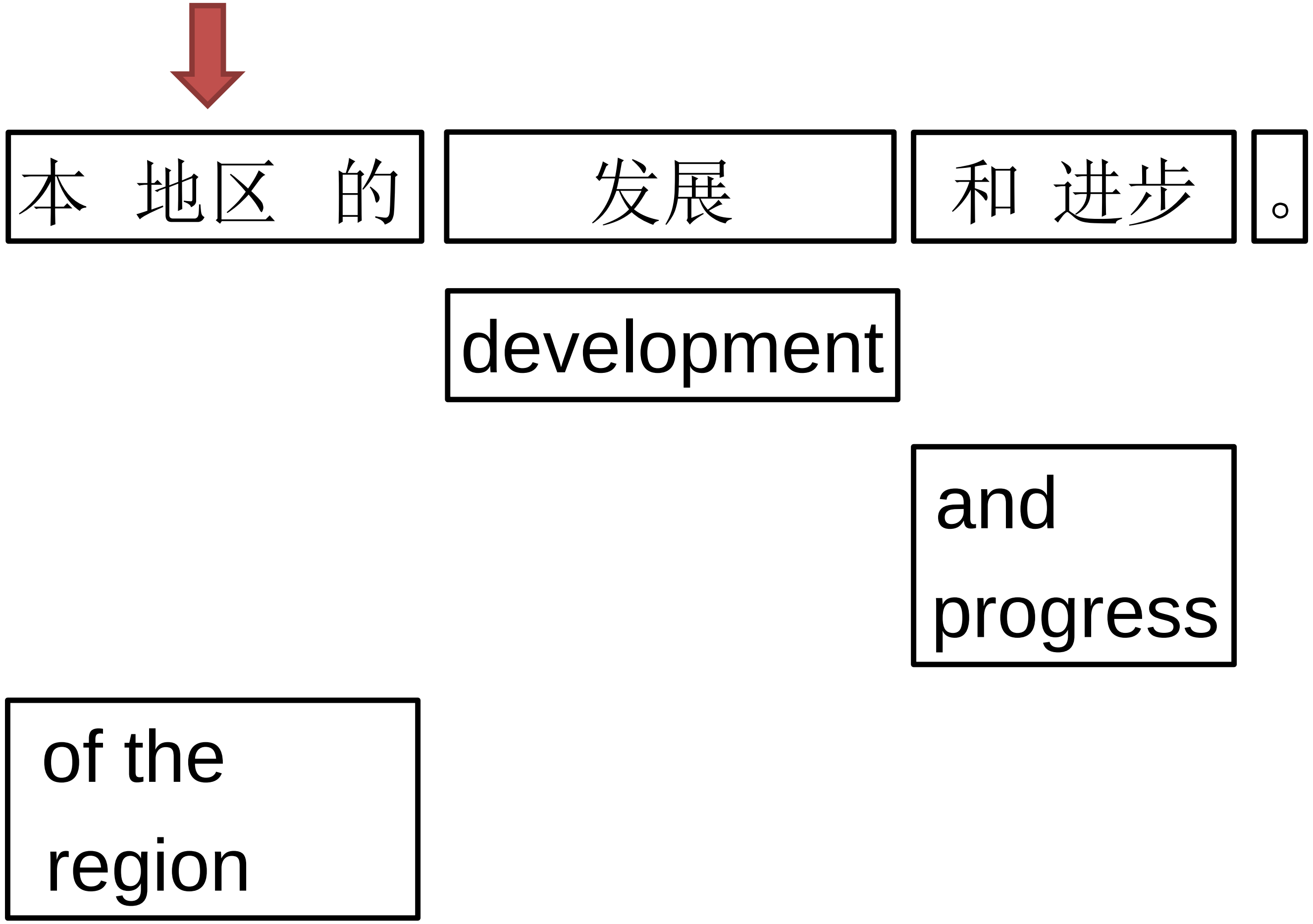
development

Monotone

and progress

p(Monotone|和 进步, and progress)

Lexicalized Reordering



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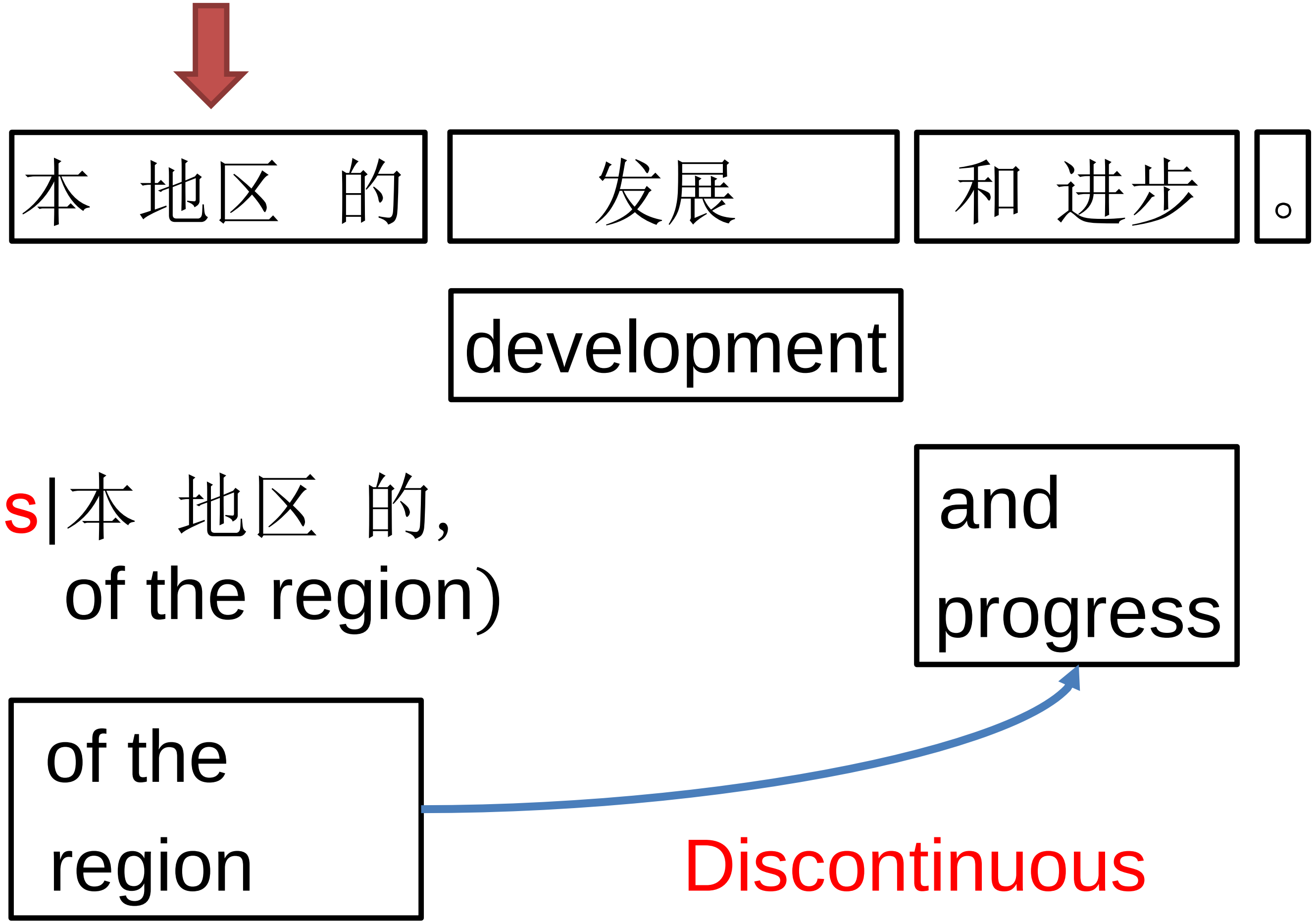
development

and progress

of the region

Lexicalized Reordering



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development

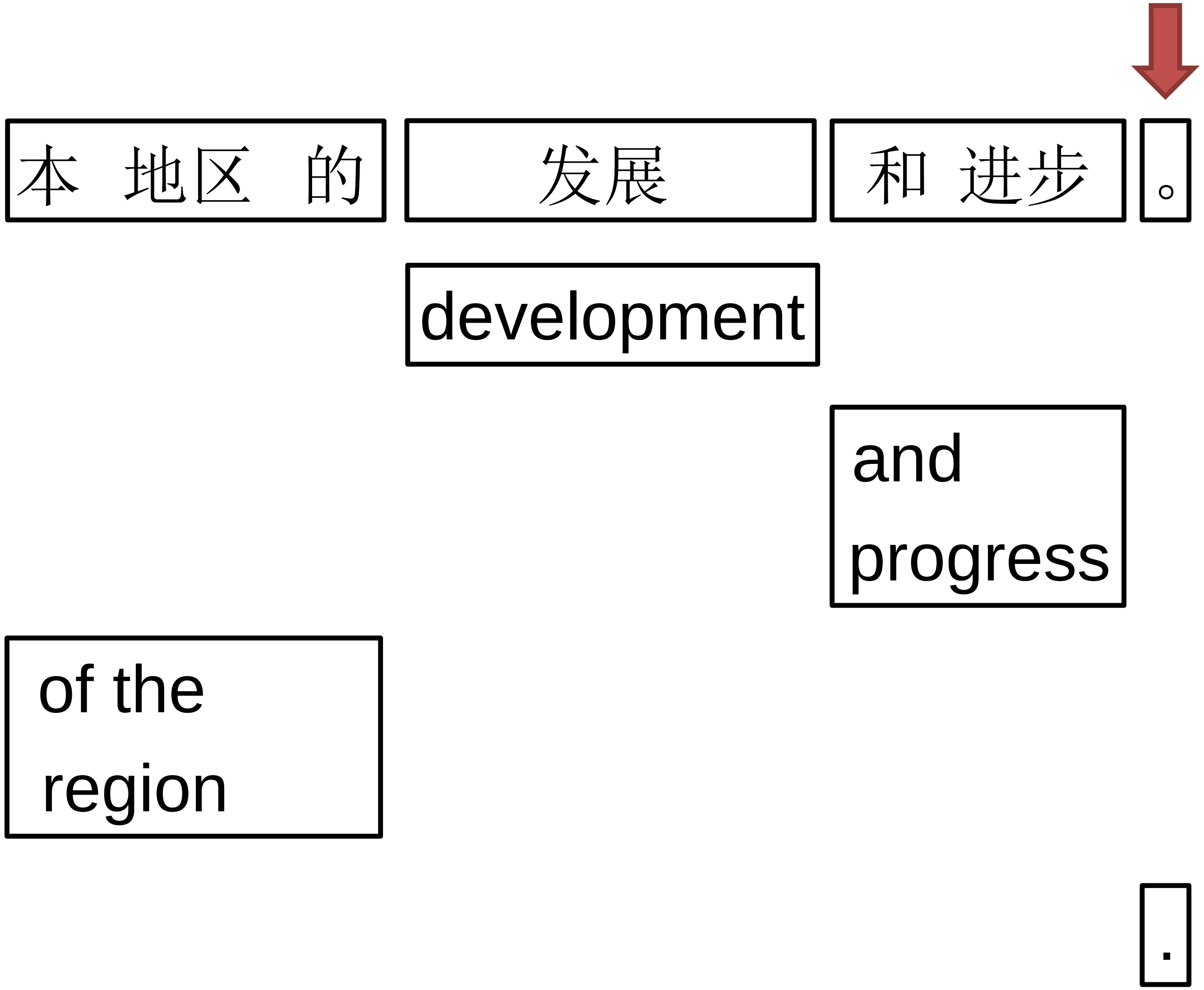
and progress

of the region

Discontinuous

p(Discontinuous|本 地区 的, of the region)

Lexicalized Reordering



本 地区 的

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和 进步

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development

and progress

of the region

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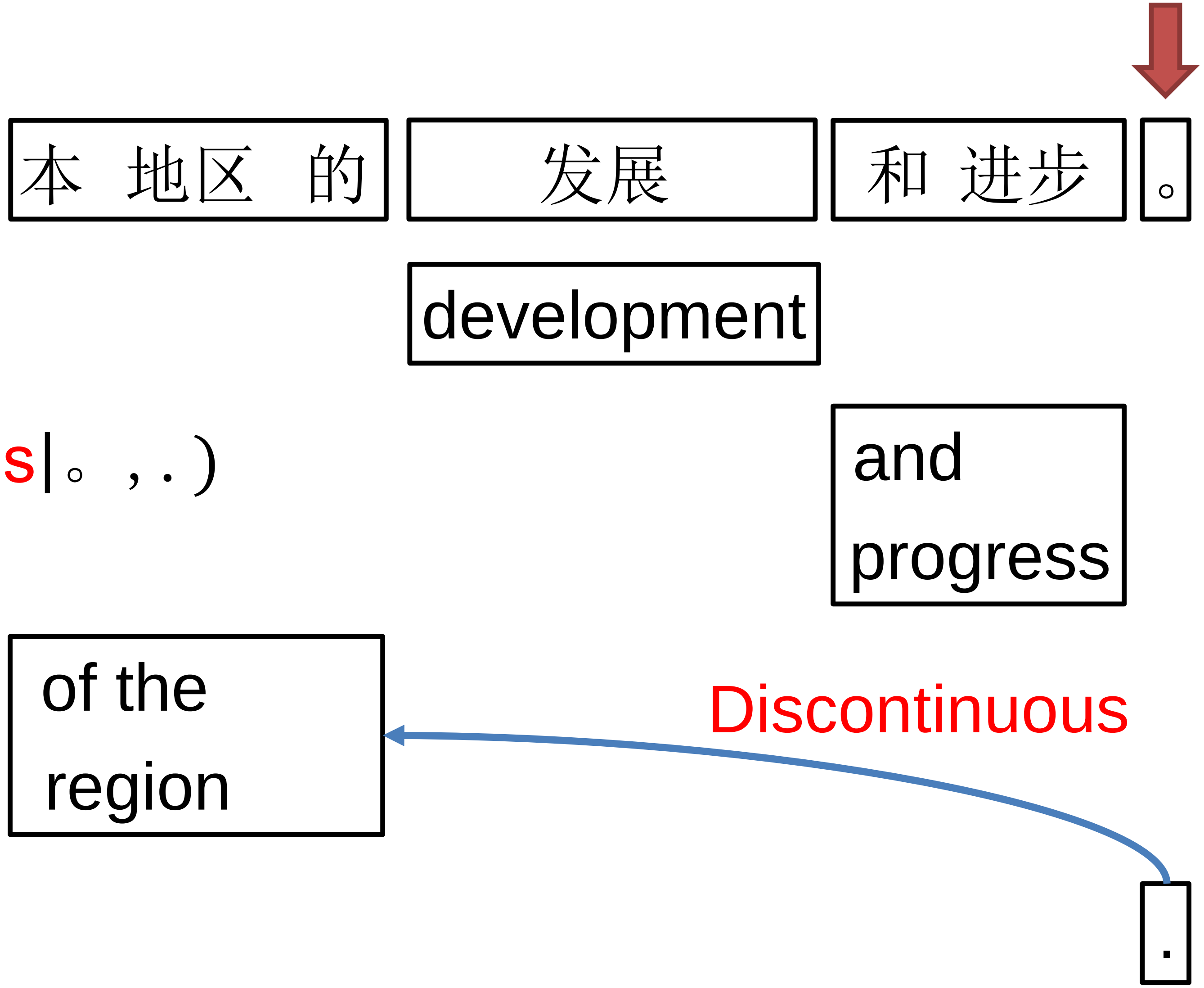
Lexicalized Reordering



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of the region

Discontinuous

.

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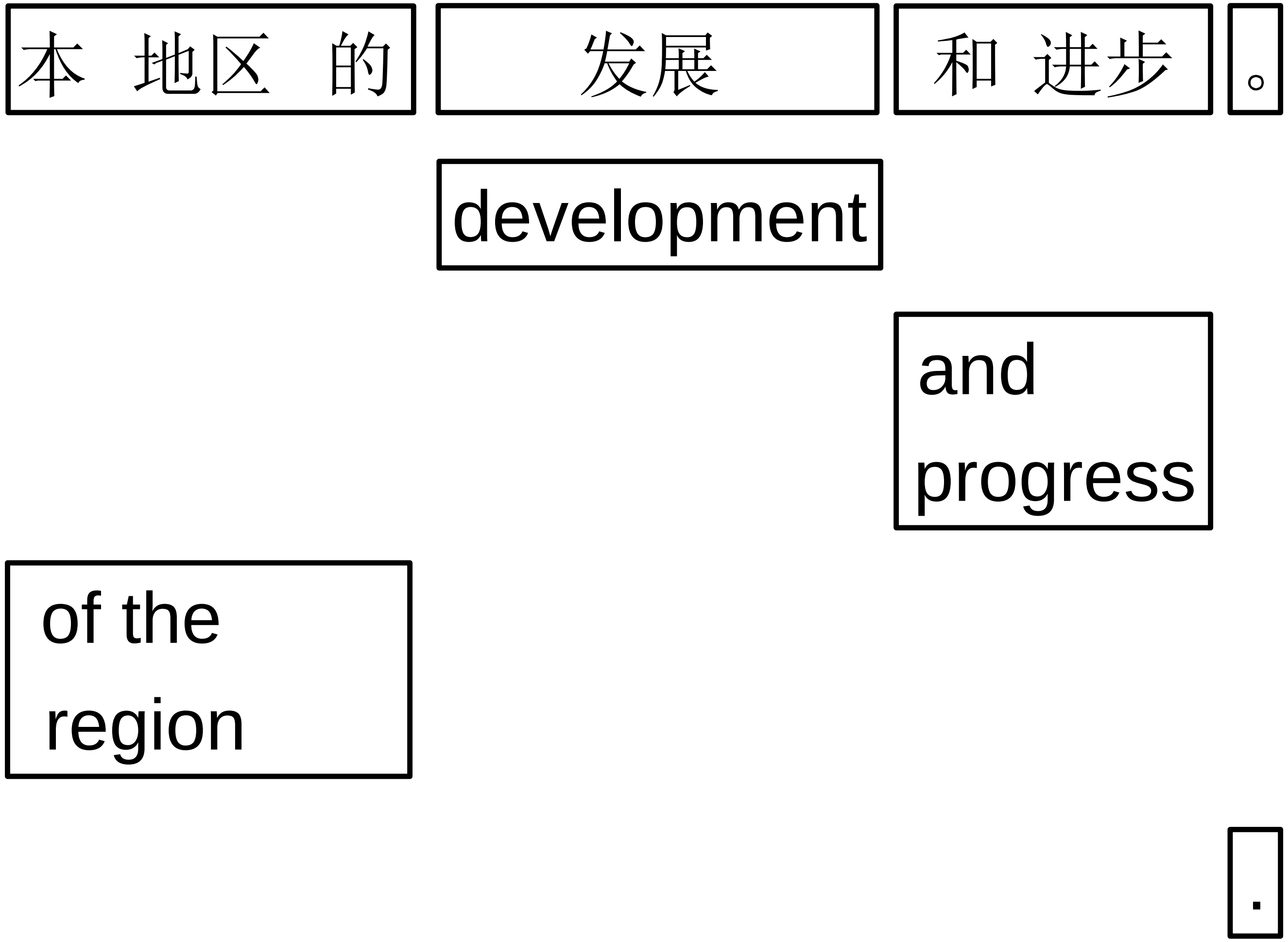
Hierarchical Lexicalized Reordering



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of the region

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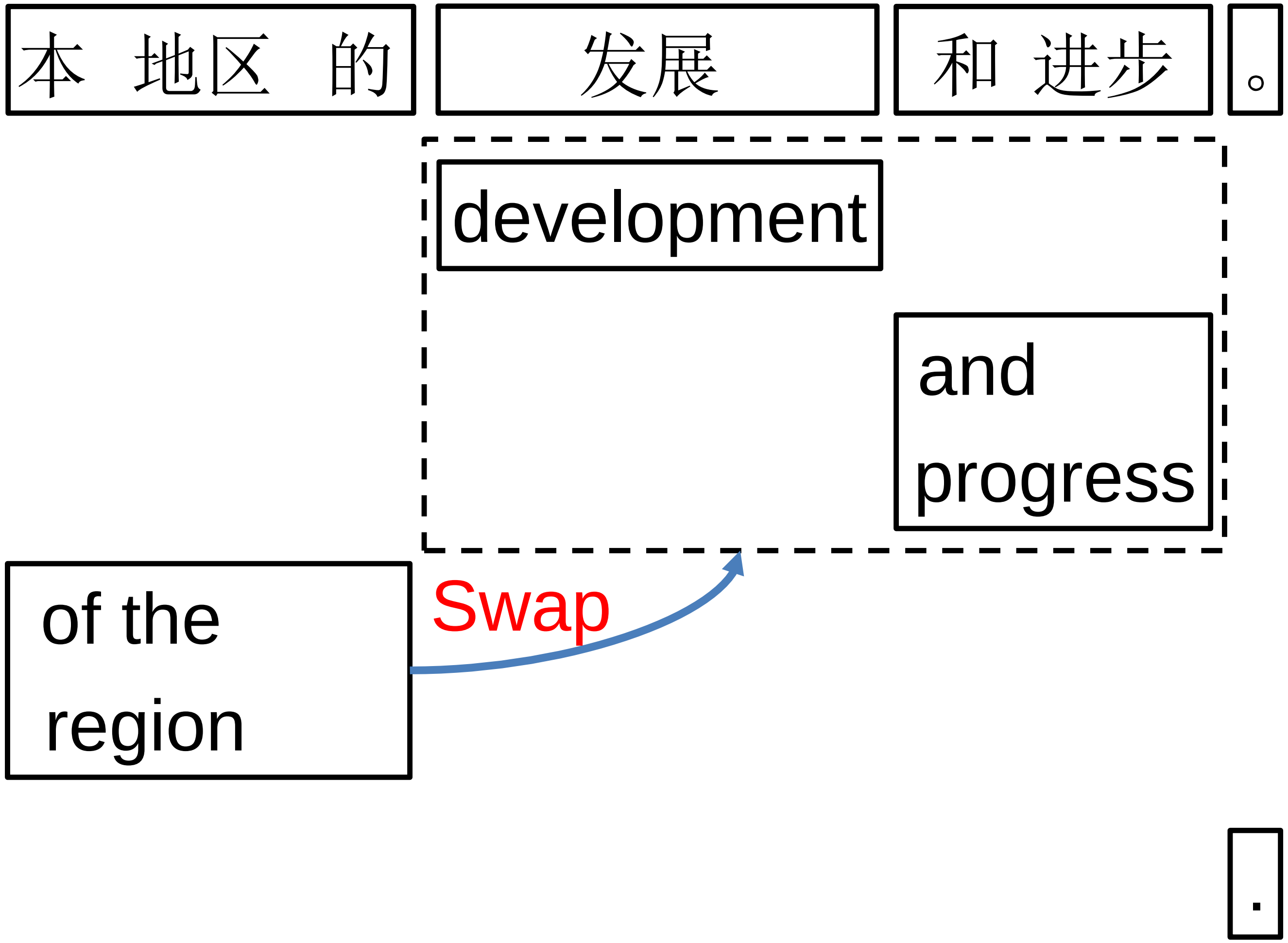
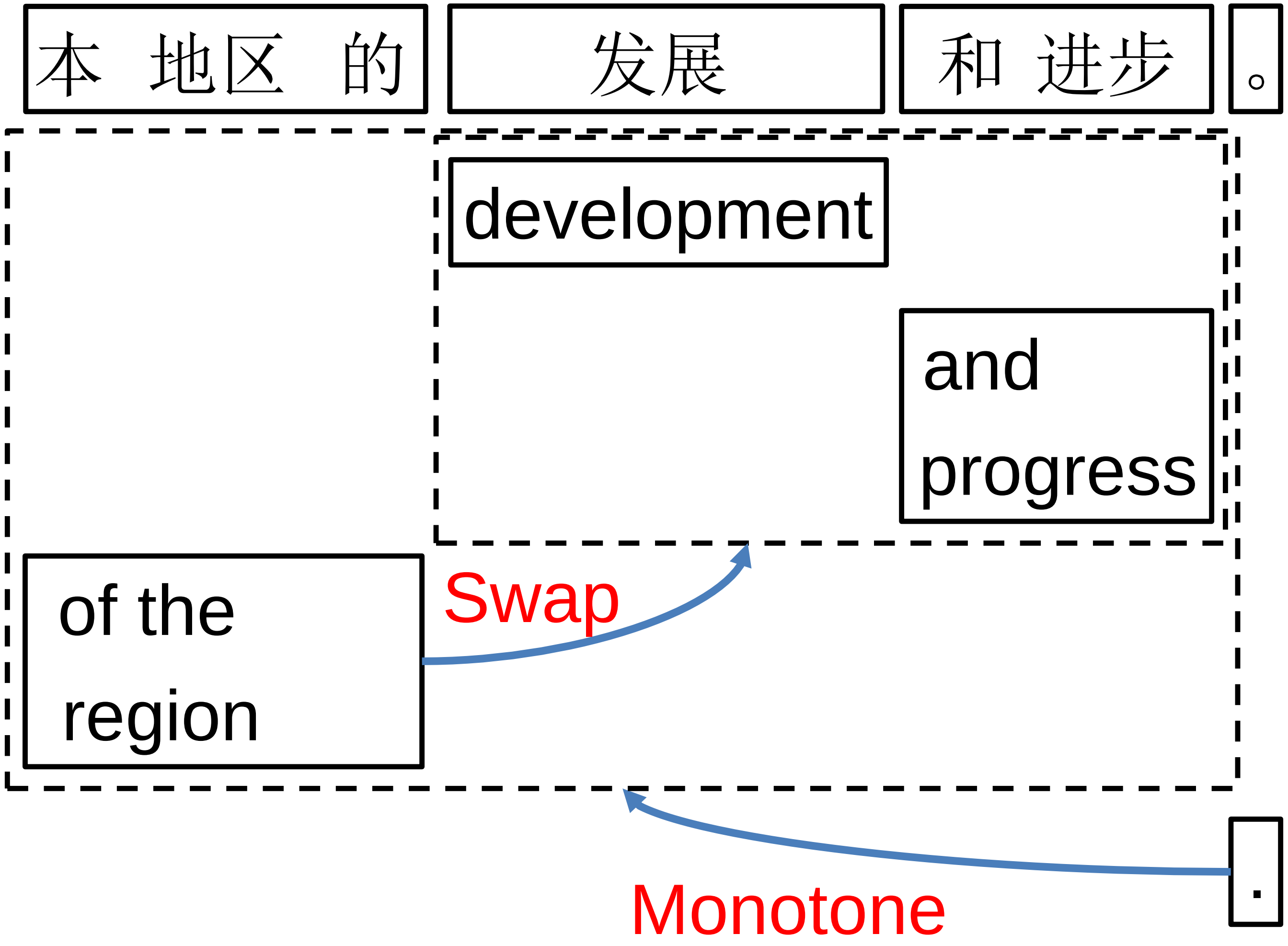
Hierarchical Lexicalized Reordering



Hierarchical Lexicalized Reordering



Hierarchical Lexicalized Reordering

p(Monotone|和 进步, and progress)

Hierarchical Lexicalized Reordering

$$\mathrm{p}(\mathrm{o}|pp) =$$

Hierarchical Lexicalized Reordering

$$\mathrm{p}(\mathrm{o}|pp) = \frac{\mathrm{count}(\mathrm{o}, pp)}{\mathrm{count}(pp)}$$

Hierarchical Lexicalized Reordering

$$\mathrm{p}(\mathrm{o}|pp) = \frac{\mathrm{count}(\mathrm{o}, pp)}{\mathrm{count}(pp)}$$

- Typically 100Ms of parameters

Hierarchical Lexicalized Reordering

$$\mathrm{p}(\mathrm{o}|pp) = \frac{\mathrm{count}(\mathrm{o}, pp)}{\mathrm{count}(pp)}$$

- Typically 100Ms of parameters
- Very sparse estimates

Hierarchical Lexicalized Reordering

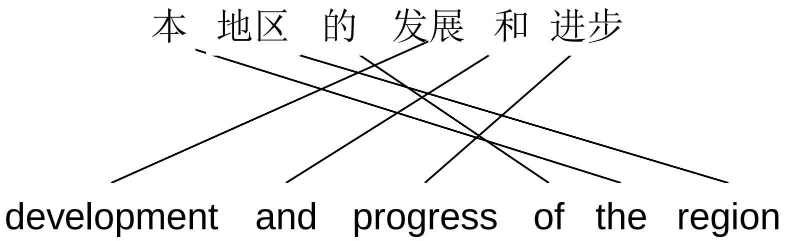
$$\mathrm{p}(\mathrm{o}|pp) = \frac{\mathrm{count}(\mathrm{o}, pp)}{\mathrm{count}(pp)}$$

- Typically 100Ms of parameters
- Very sparse estimates
- Objective: Likelihood

Hierarchical Lexicalized Reordering

$$\mathrm{p}(\mathrm{o}|pp) = \frac{\mathrm{count}(\mathrm{o}, pp)}{\mathrm{count}(pp)}$$

- Typically 100Ms of parameters
- Very sparse estimates
- Objective: Likelihood
- Training data: word-aligned bi-texts



MaxEnt Reordering (Xiong 2006, Nguyen 2009)

$\mathrm{p}(\mathrm{o}|pp) =$ indicator features!

e.g. Monotone_progress,
Monotone_和

MaxEnt Reordering (Xiong 2006, Nguyen 2009)

$$\mathrm{p}(\mathrm{o}|pp) = \frac{\exp\{\theta^T h(\mathrm{o}, \mathrm{pp})\}}{\sum_o \exp\{\theta^T h(o, \mathrm{pp})\}}$$

e.g. Monotone_progress,
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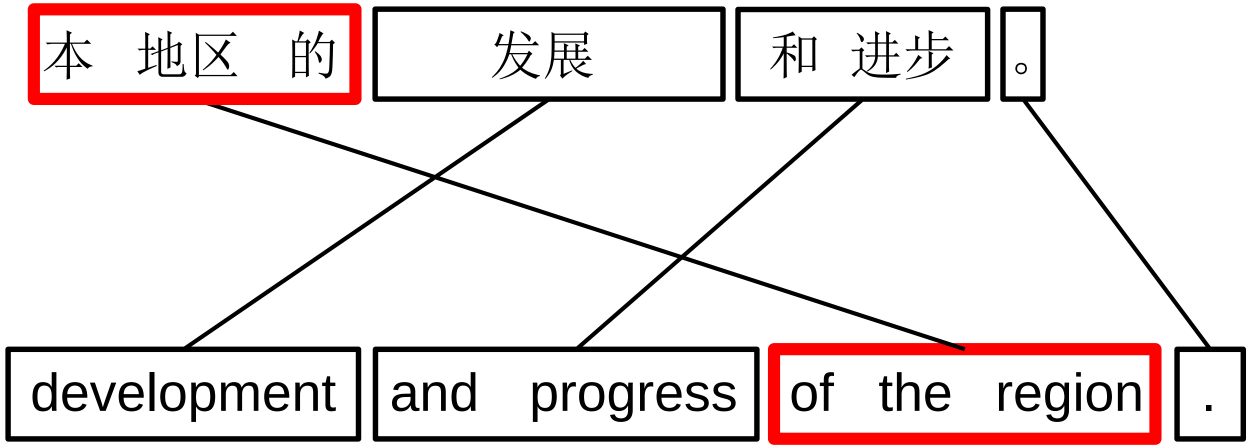
e.g. Monotone_progress,
Monotone_和

- Typically Ms of parameters
- *Better estimates*
- Objective: Likelihood
- Training data: word-aligned bi-texts

Sparse Reordering (Cherry 2013)

- Simple unigram features
- Most frequent 80 words, 20 or 50 class Brown Clusters
  e.g., Monotone_the, Monotone_C20, Monotone_C50
- About 3.5K features



- Discontinuous_src_本
- Discontinuous_tgt_of
- Discontinuous_src_C20
- …

Sparse Reordering (Cherry 2013)

Idea: Add ordering features to top-level features and tune with MIRA

$$\hat{e} = \mathrm{argmax}_e \theta^T h(f, e)$$

- *Better estimates*

Sparse Reordering (Cherry 2013)

Idea: Add ordering features to top-level features and tune with MIRA

$$\hat{e} = \mathrm{argmax}_e \theta^T h(f, e)$$

h_1: p(e|f)
h_2: p(f|e)
h_3: $p_{LM}(e)$

- *Better estimates*

Sparse Reordering (Cherry 2013)

Idea: Add ordering features to top-level features and tune with MIRA

$$\hat{e} = \mathrm{argmax}_e \theta^T h(f, e)$$

- *Better estimates*

h_1: p(e|f)
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h_3: $p_{LM}(e)$
h_4: c(Monotone_progress)
h_5: c(Monotone_和)
…

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…

- *Better estimates*
- Objective: **BLEU**

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Idea: Add ordering features to top-level features and tune with MIRA

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…

- *Better estimates*
- Objective: **BLEU**
- Training data: **machine translation output**

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h_3: $p_{LM}(e)$
h_4: c(Monotone_progress)
h_5: c(Monotone_和)
…

- *Better estimates*
- Objective: **BLEU**
- Training data: **machine translation output**
- Much better than MaxEnt

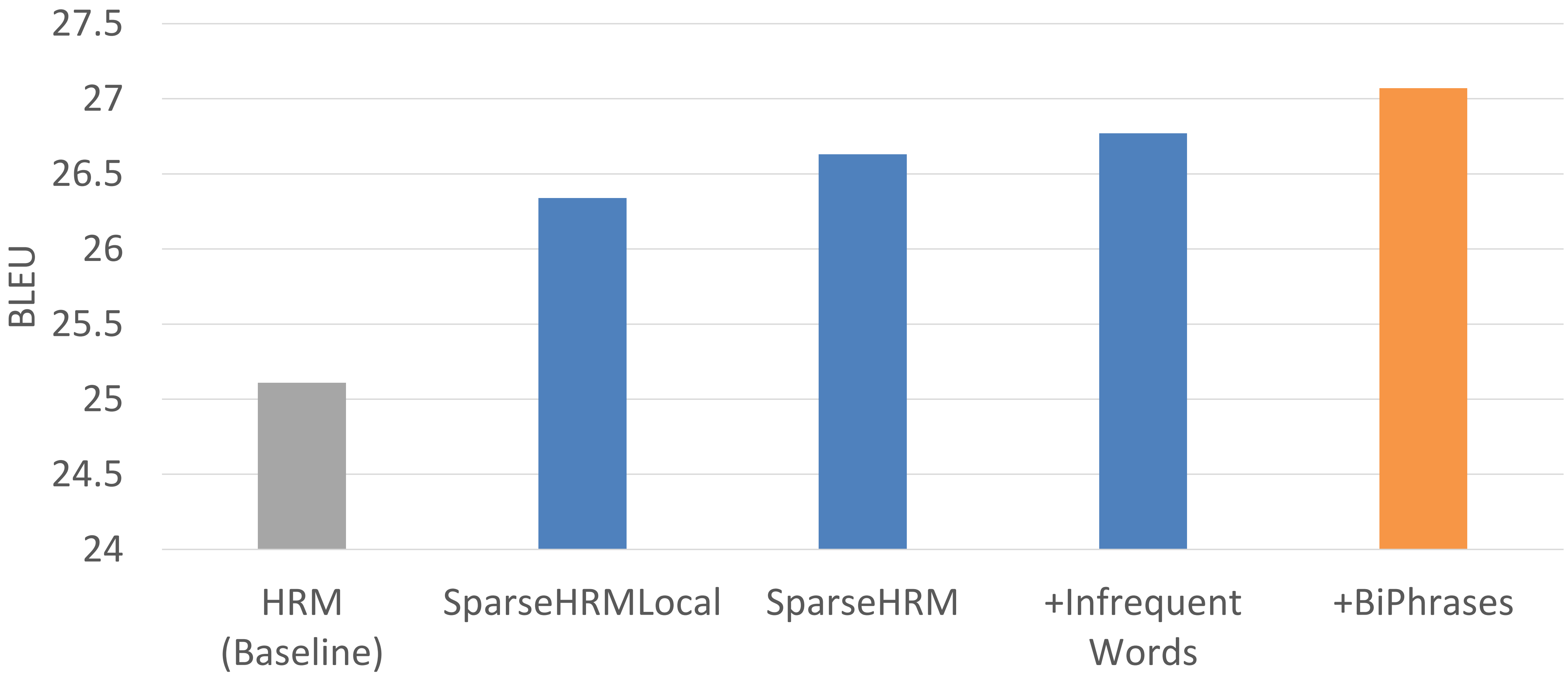
Sparse Reordering (Cherry 2013)

- Lexicalized models trained on Ms of sentences with 100Ms of parameters
- Cherry (2013): Ordering model with 3.5K features learned on 2K sentences
- Can we learn a general purpose ordering model this way?
- MIRA/PRO don’t scale to truly large settings (Yu 2013, Eidelman 2013)
- **Next:** Large-scale discriminative models with Ms of features trained on 100Ks of sentences using expected BLEU

Scaling the feature set

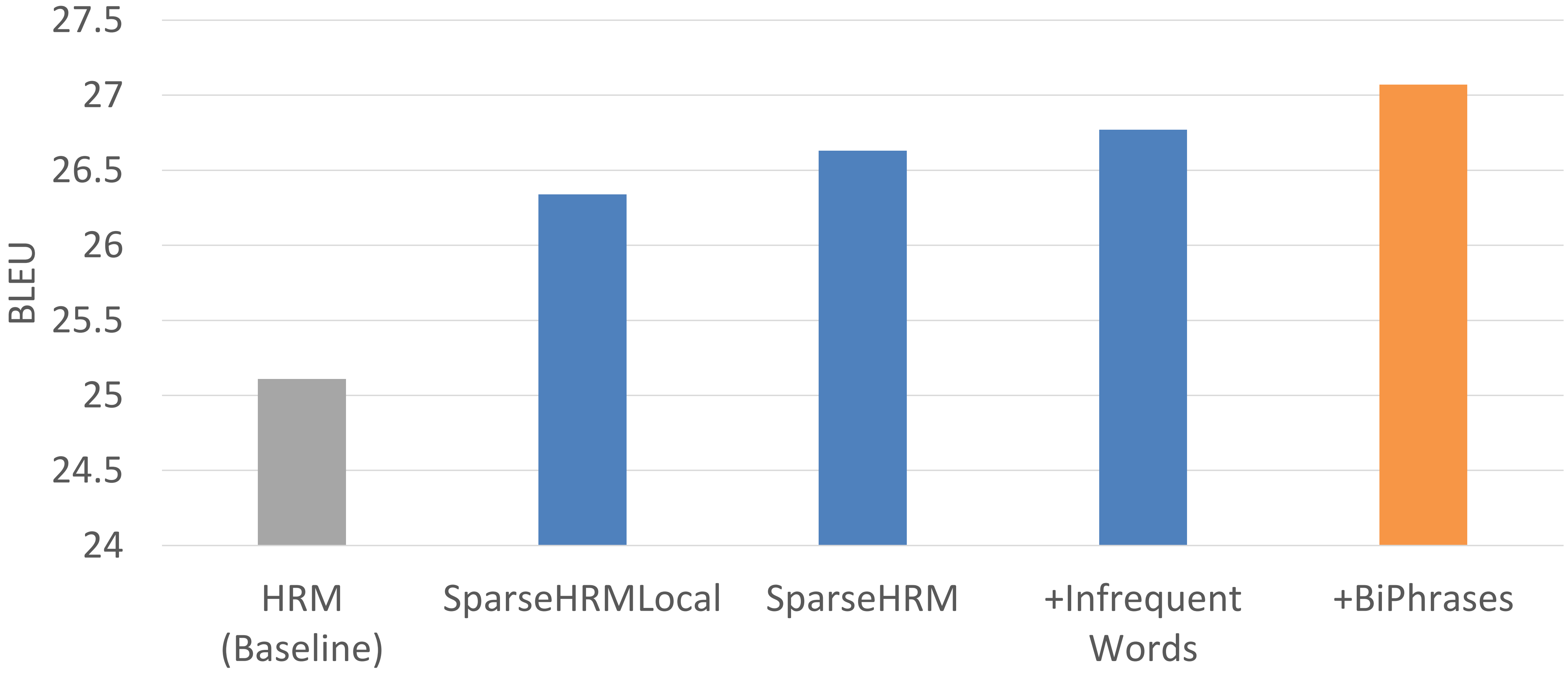
Features	4.5K	9K	900K	3M

Scaling the feature set



Features 4.5K 9K 900K 3M

Scaling the feature set



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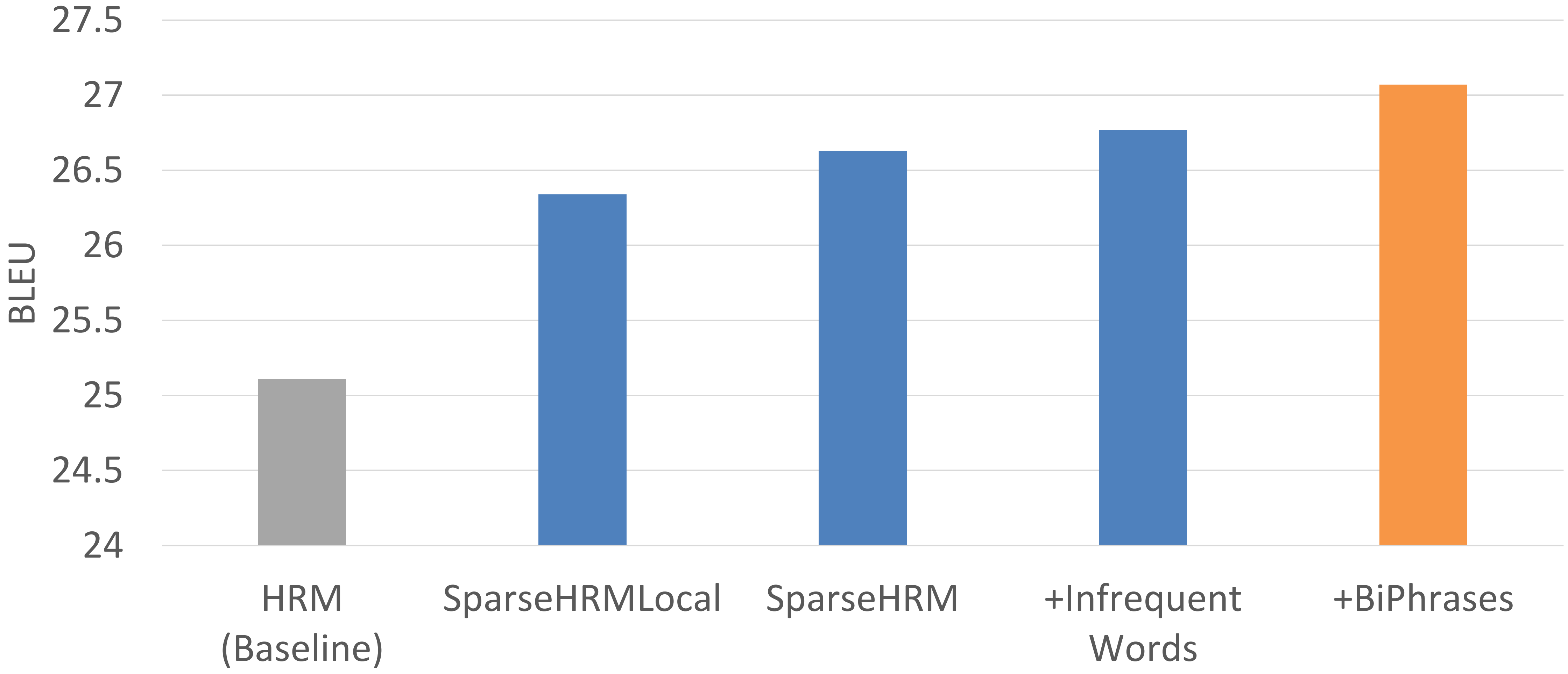
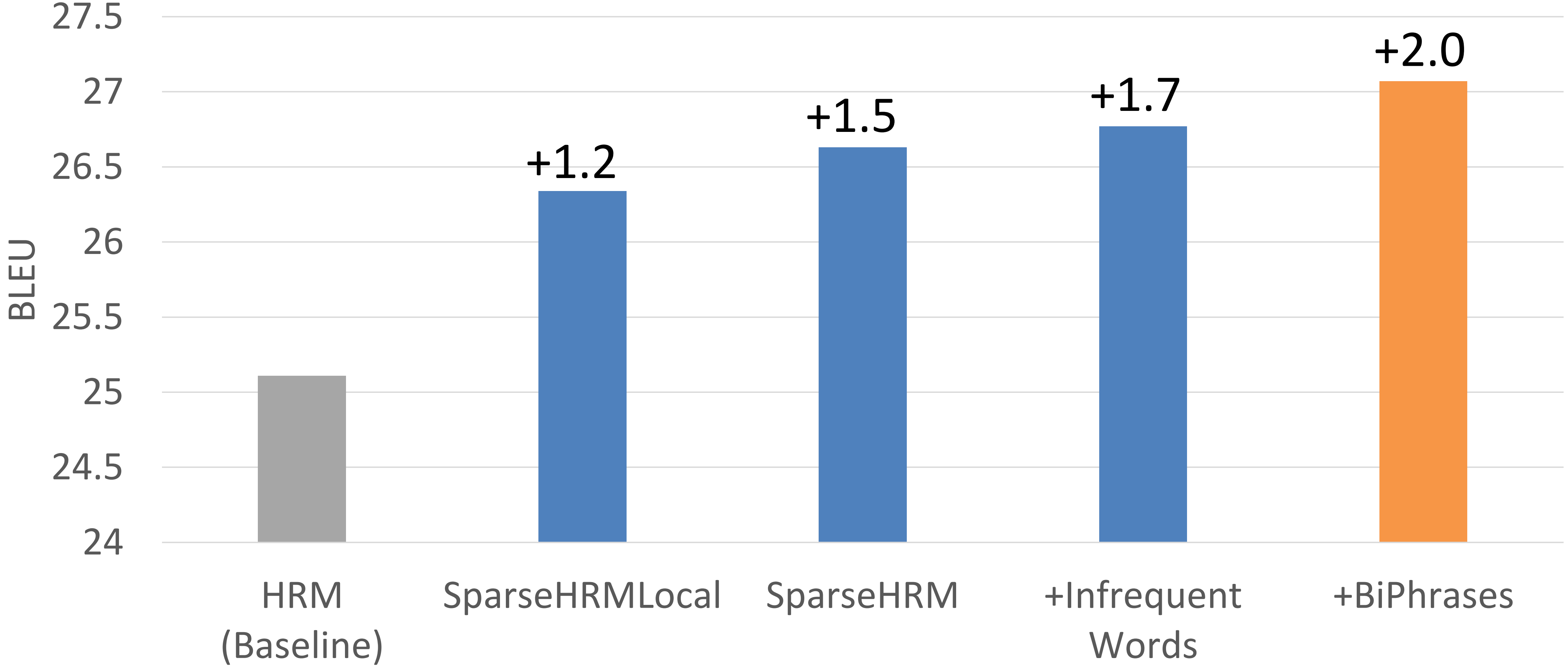


Features 4.5K 9K 900K 3M

Scaling the feature set



Features	4.5K	9K	900K	3M

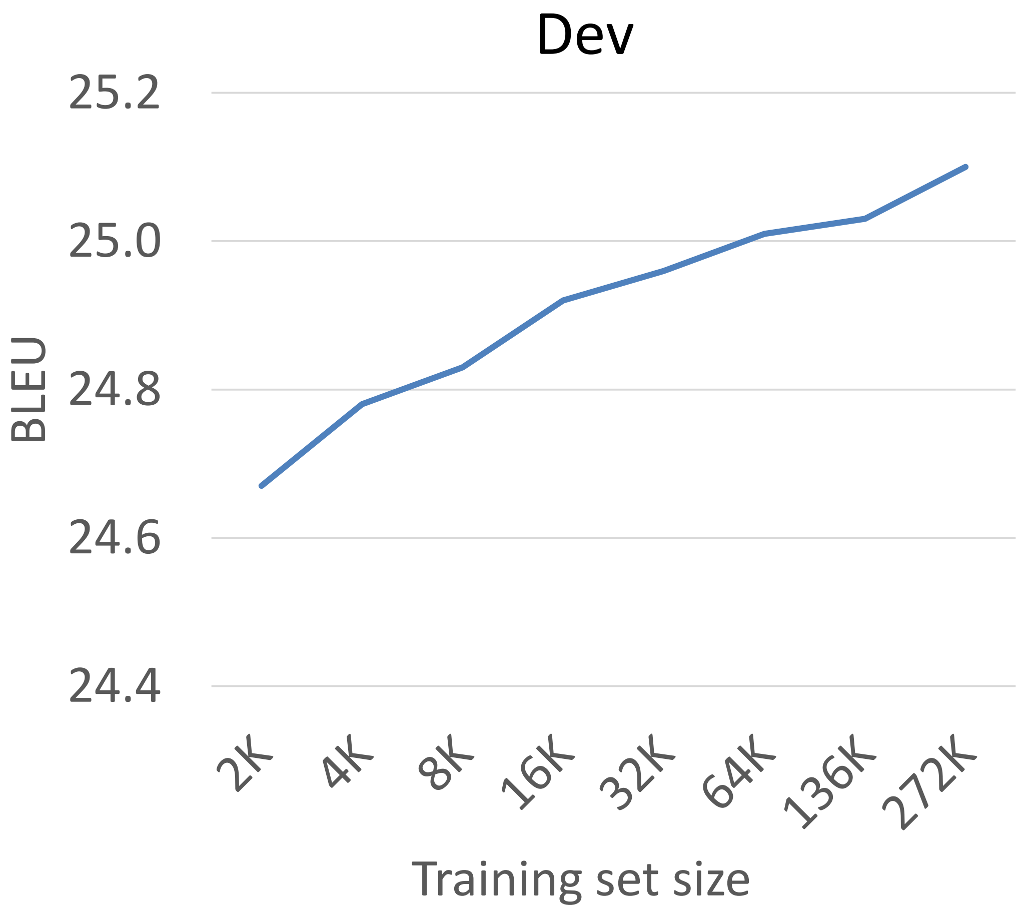
Scaling the training data

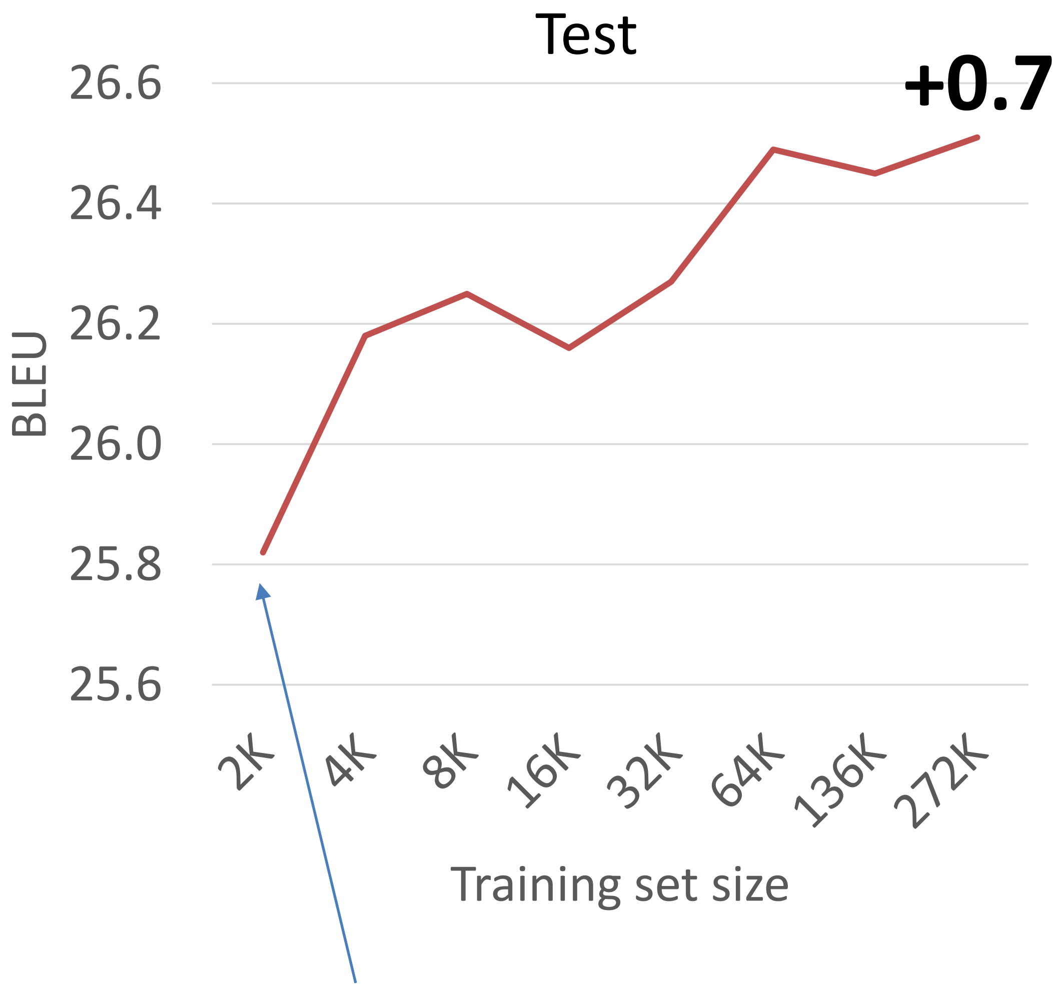
Dev

Test

N-best rescore with SparseHRMLocal (4.5K features)

Scaling the training data





N-best rescore with SparseHRMLocal (4.5K features)

Setup of Cherry (2013)

Why is this better than Lexicalized/Maxent models?

- Objective: Likelihood → BLEU
- Train data: bilingual corpus → machine translation output

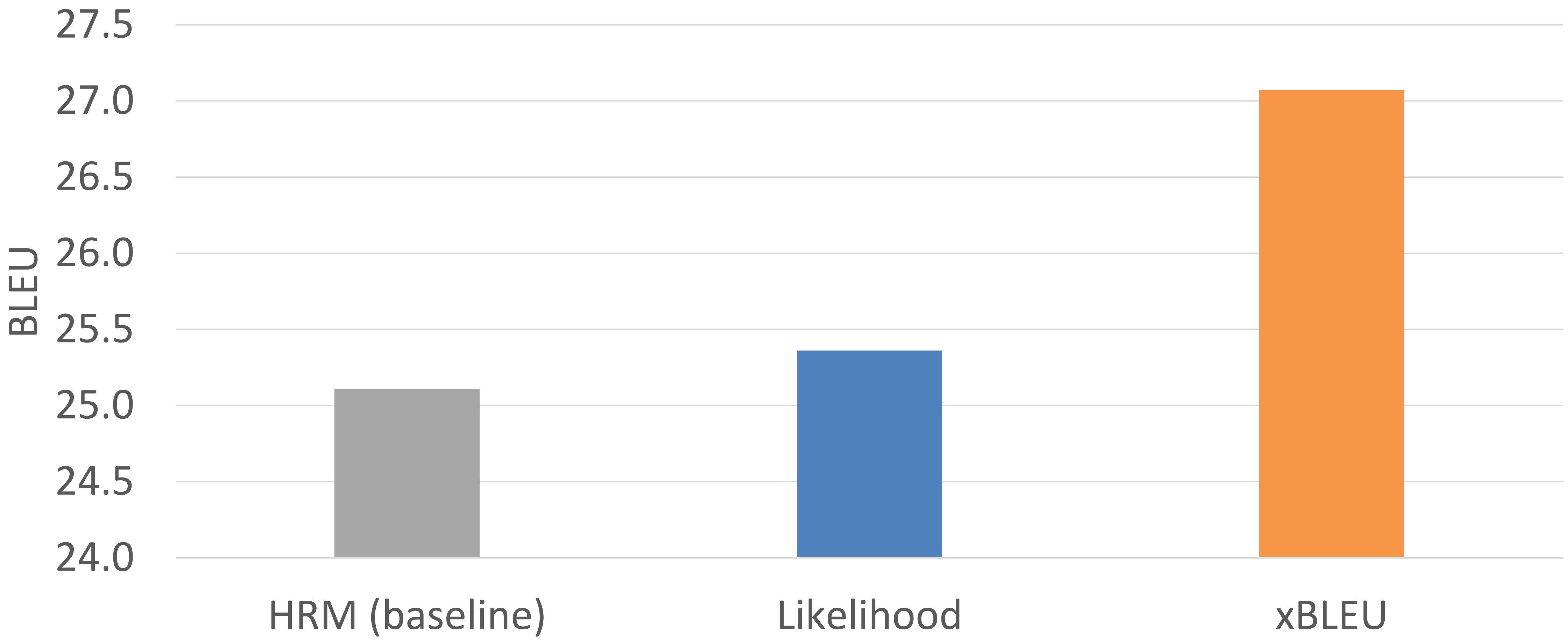
- Which one responsible for better performance?

- Experiment: Likelihood/xBLEU train on MT output

Likelihood vs. xBLEU

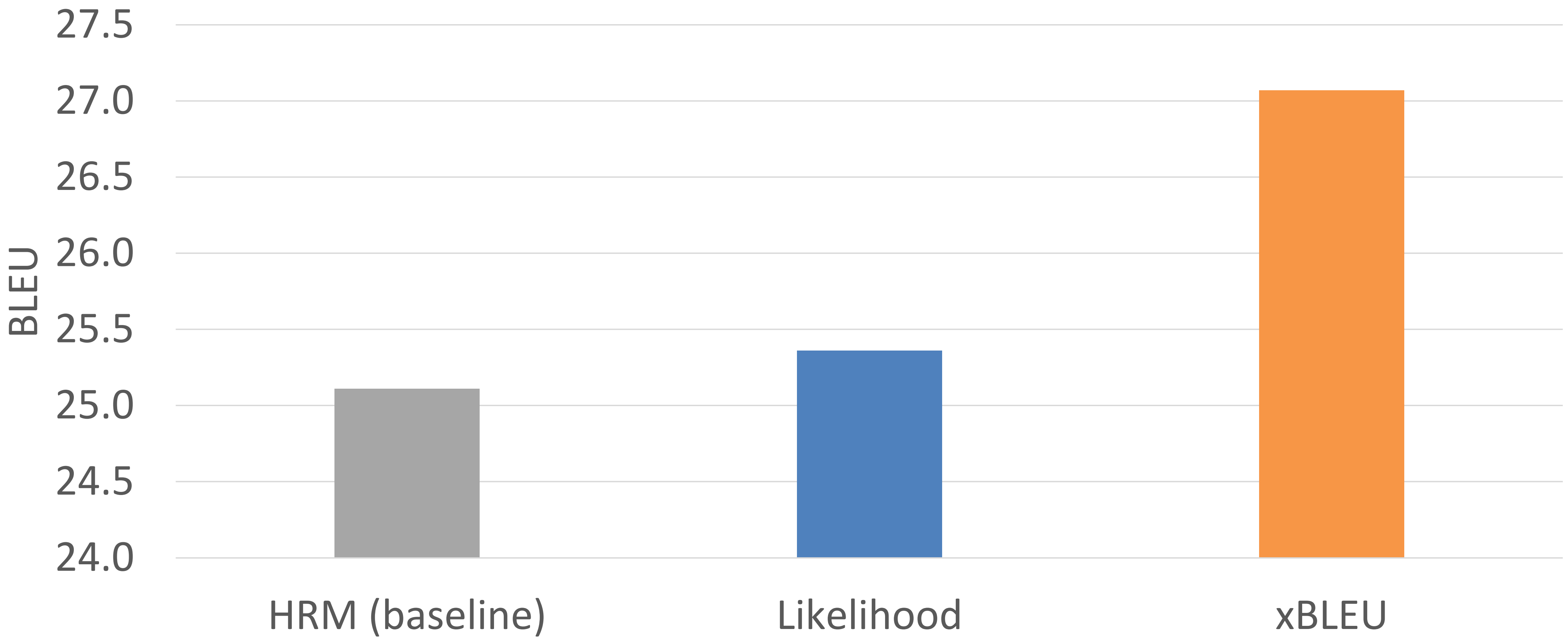
Based on BiPhrases (3M features)

Likelihood vs. xBLEU



Based on BiPhrases (3M features)

Likelihood vs. xBLEU



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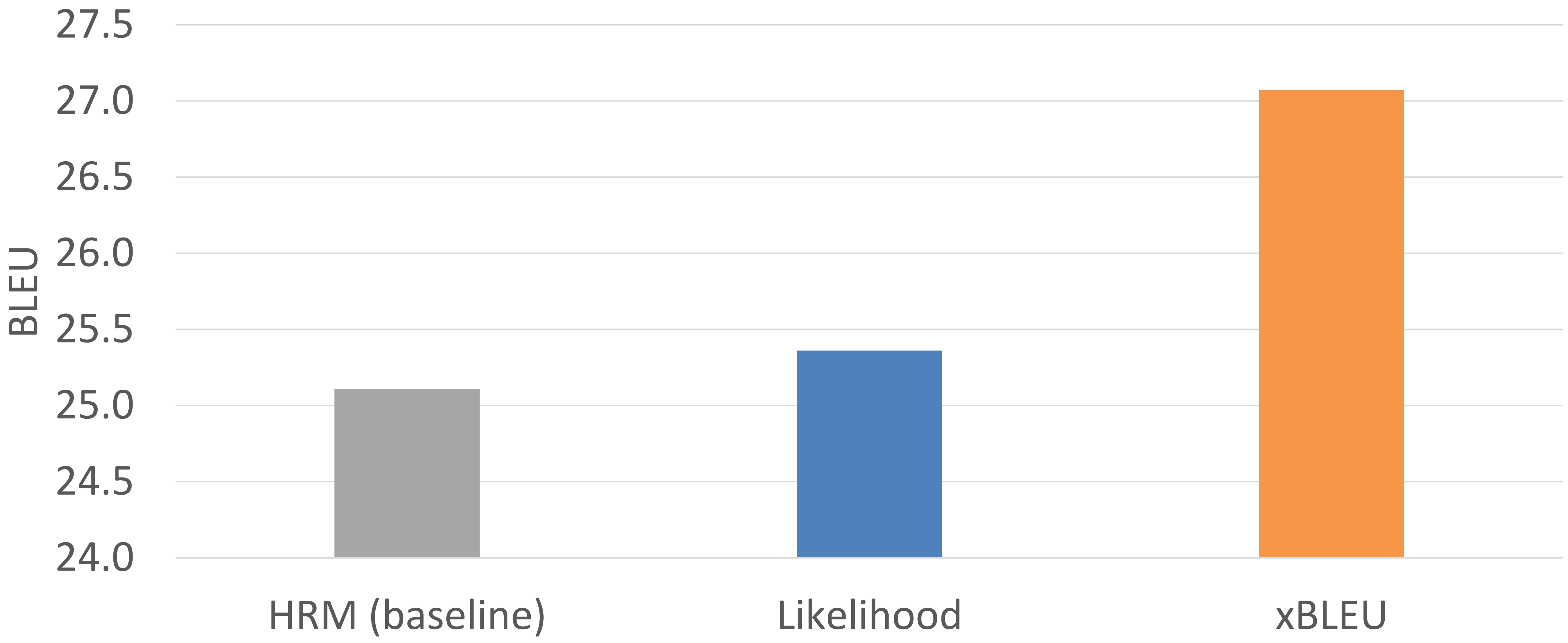

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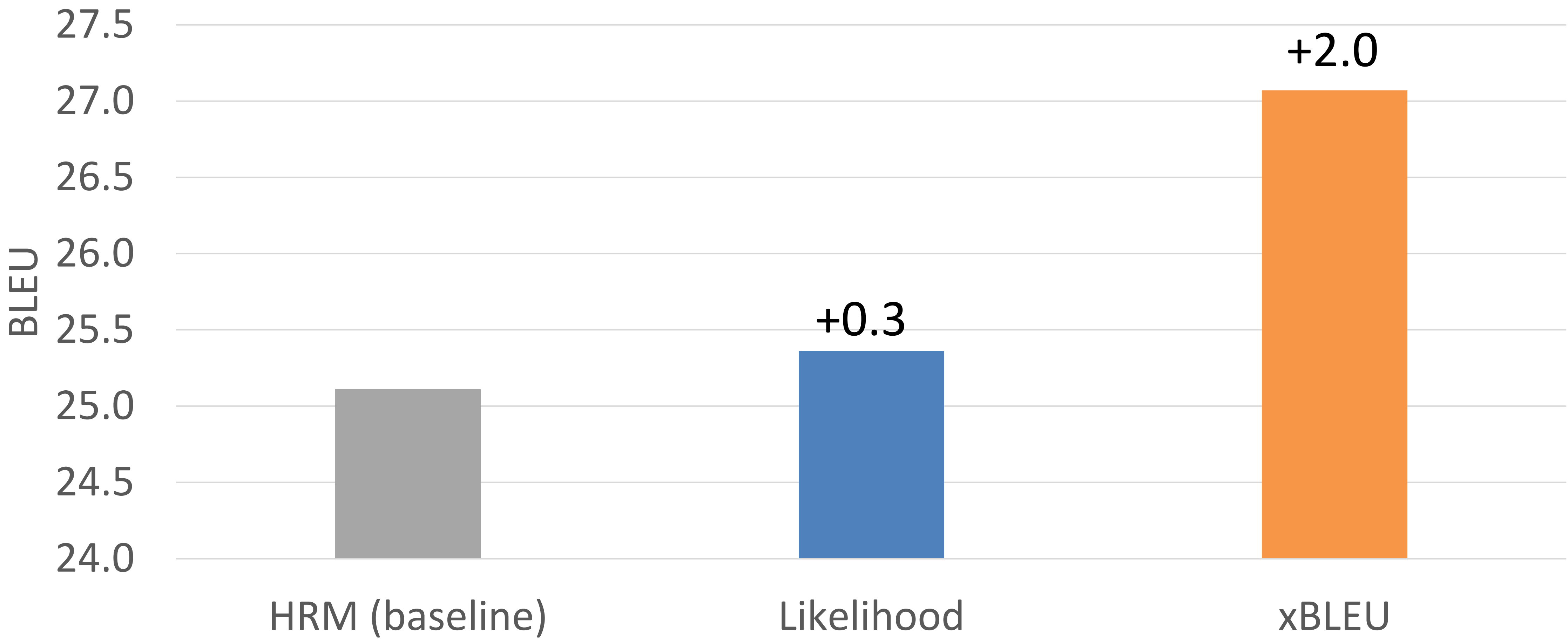

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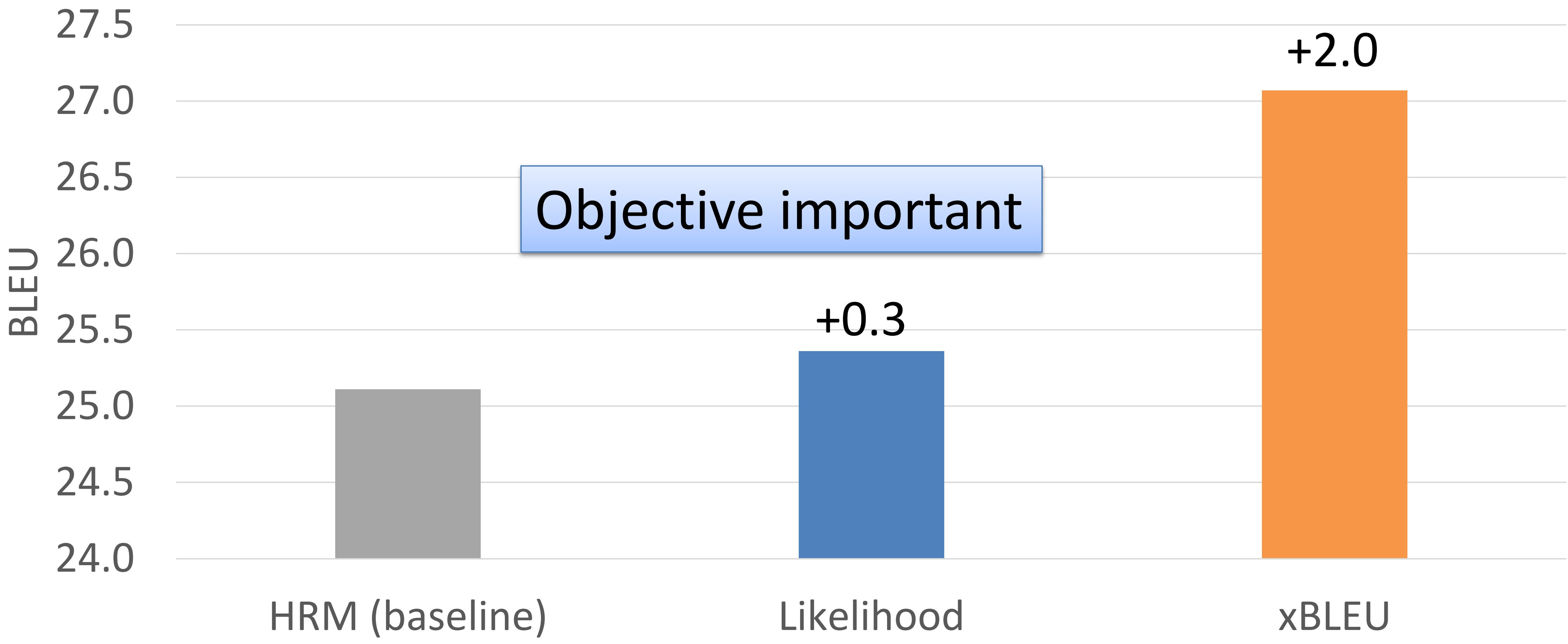


Objective important

Based on BiPhrases (3M features)

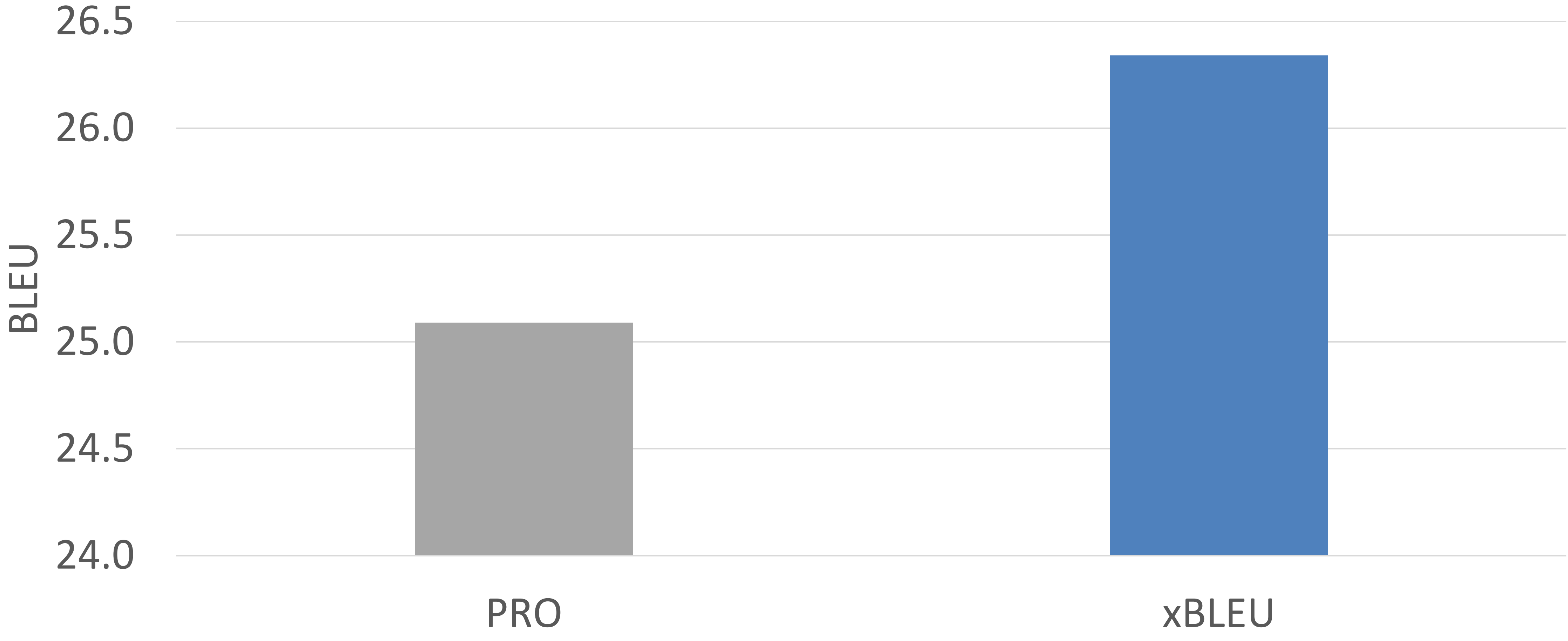
xBLEU vs. PRO

Based on SparseHRMLocal (4.5K features)

Train Data: 2.5K 140K

xBLEU vs. PRO

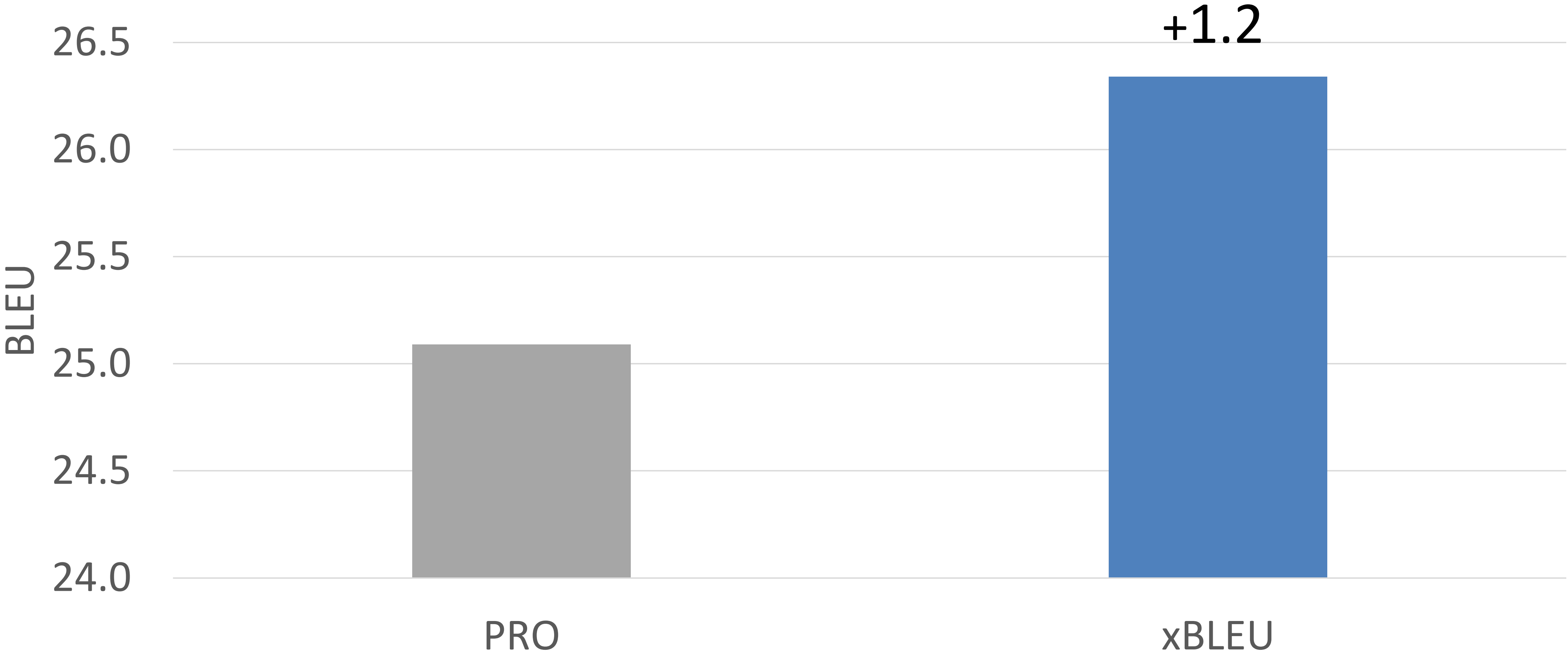
Based on SparseHRMLocal (4.5K features)



Train Data: 2.5K 140K

xBLEU vs. PRO

Based on SparseHRMLocal (4.5K features)



Train Data: 2.5K 140K

Comparison to Max-Violation Perceptron

	Max-Violation Perceptron	xBLEU

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Comparison to Max-Violation Perceptron

	Max-Violation Perceptron	**xBLEU**
Loss	No partial credit (0/1)	**partial credit**
Train data	Mostly short sentences (reference must be reachable)	Uses **all data**
Updates	Based 1-best and reference	Based on **all outputs** in gen-set

Summary

- Directly optimizing sub-models towards BLEU improves translation accuracy
- xBLEU allows estimation of millions of features
- More training data helps
- Objective crucial to good performance

Conclusion

- Recurrent nets are very well suited to model translation
- They complement and improve simpler models
- xBLEU training effective for both neural nets and linear models
- xBLEU scales to millions of features on hundreds of thousands of sentences

Future Directions

What can we do with the presented methods?

- LSTM nets for translation
- Recurrent nets for other NLP tasks, e.g., CCG parsing
- xBLEU training: Large-scale discriminative training of all models

Thank you!