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Learning Latent Topic Information for Language Model Adaptation in Statistical Machine Translation

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Outline

- Task
- Problems
- Our Approach
- Experiments
- Conclusion

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Language Model Adaptation in SMT

- Two category
  - **Selecting similar training data for current translation task**
  - **Modify the LM parameter itself**

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Data selection based LM Adaptation

- Framework
  - **The generic LM** $P_g(w_i|h)$ **;**
    - Estimated by the whole LM training corpus
  - **The bias LM** $P_b(w_i|h)$ **;**
    - Estimated by the selected similar training data from LM training corpus
  - **The adapted LM** $P_a(w_i|h)$ **;**
    - used for SMT system

$$P_a(w_i|h) = \gamma P_g(w_i|h) + (1-\gamma) P_b(w_i|h)$$

How to select the similar training data?

- Monolingual approach
  - **First pass translation hypotheses s**
- Cross-lingual approach
  - **Candidate translation sentence s**
- Framework

  The sentence in the LM training corpus S

  Similarity(s,S): The similarity between s and S

Data selection based LM Adaptation

- Traditional approach
  - **TF-IDF;**
  - **Centroid similarity;**
  - **Cross-entropy difference;**
  - **Cross-lingual information retrieval;**
  - **Cross-lingual similarity**

Data selection based LM Adaptation

- Traditional approach
  - **TF-IDF;**
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  - **Cross-lingual information retrieval;**
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- General Characteristics
  - **Perform at the word level**
  - **Exact only term matching schemes**

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  - **Centroid similarity;**
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  - **Cross-lingual information retrieval;**
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- General Characteristics
  - **Perform at the word level**
  - **Exact only term matching schemes**
- Main problem
  - **Do not consider word-topic and word-distribution information**

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Latent Topic Based Data Selection Model

- Learning word-topic and word-distribution information by Latent Dirichlet Allocation (LDA) Model
  - **Step 1, estimate word-topic information of the whole LM training corpus;**
  - **Step 2, infer the word-topic information first pass translation hypotheses ;**
  - **Step 3, compute the similarity and select the similar sentences.**

Latent Topic Based Data Selection Model

- Learning word-topic and word-distribution information by Latent Dirichlet Allocation (LDA) Model
  - **Step 1, estimate word-topic information of the whole LM training corpus;**
  - **Step 2, infer the word-topic information first pass translation hypotheses ;**
  - **Step 3, compute the similarity and select the similar sentences.**
- Similarity Computation
  - **Step 1, compute the sentence-topic** $P_{LT}(z|s) = \frac{1}{|s|}\sum_{w \in s} P(z|w)$
  - **Step 2, compute topic based sentence similarity**

$$
\begin{aligned}
P_{LT}(s|S) &= \sum_{z} P_{LT}(s|z)P_{LT}(z|S) \\
&= \sum_{z \in K} \frac{P_{LT}(z|s)P(s)}{P(z)} P_{LT}(z|S) \\
&= \frac{K}{N} \sum_{z \in K} P_{LT}(z|s)P_{LT}(z|S)
\end{aligned}
$$

Parameter Estimation (LDA model)

- How to select proper topic number?

$$Perplexity(C) = exp\{-\frac{\sum_{(s,w)\in C} lnP(w|s)}{|C|}\}$$

$$P(w|s) = \sum_{z=1}^{K} P(w|z)P(z|s)$$

Latent Topic based Cross-Lingual Data Selection Model

- Sentence projection
  - **u: source sentence; v: target sentence;**
  - Σ **:bilingual word co-occurrence matrix**
  - **Computing projection:**

$$\hat{v} = u\Sigma$$

$\hat{v}$ is emphasized that most frequently co-occur with the source term in u

Latent Topic based Cross-Lingual Data Selection Model

- Sentence projection
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- Cross-lingual sentence similarity

$\hat{v}$ **as the first pass translation hypotheses** $\hat{s}$,

$$P_{CLLT}(\hat{s}|S) = \frac{K}{N}\sum_{z\in K} P_{CLLT}(z|\hat{s})P_{CLLT}(z|S)$$

Combining Latent Topic with TF-IDF for Data Selection

- Combine these two approach together

$$P_{LT\_TF-IDF}(s|S) = \mu P_{LT}(s|S) + (1-\mu)P_{TF-IDF}(s|S)$$

$$P_{CLLT\_CLS_s}(\hat{s}|S) = \lambda P_{CLLT}(\hat{s}|S) + (1-\lambda)P_{CLS_s}(\hat{s}|S)$$

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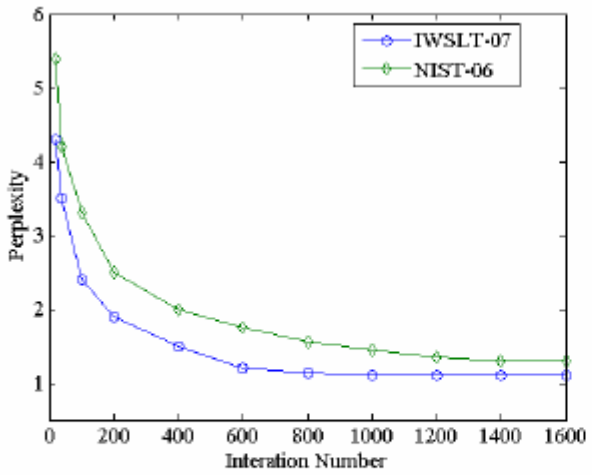
Framework

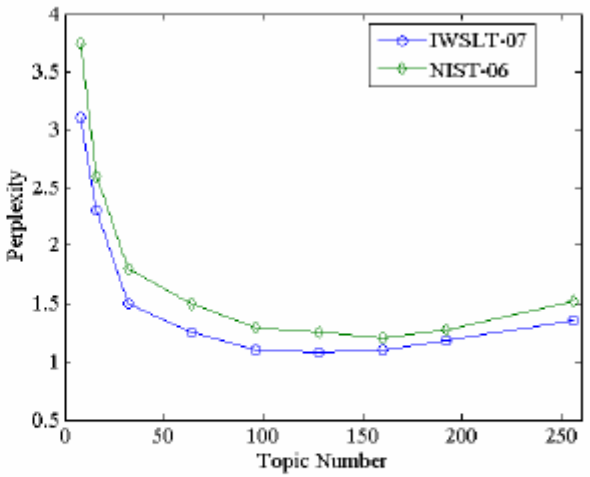
- Comparing adapted LMs with the generic LM
  - **reference translations based perplexity**
  - **SMT performance**
- Data sets
  - **IWSLT-07 (dialogue domain)**
  - **NIST-06 (news domain)**

Iteration and Topic Number Selection

- IWSLT-07 96 topics and 1000 iterations
- NIST-06 168 topics and 1400 iterations



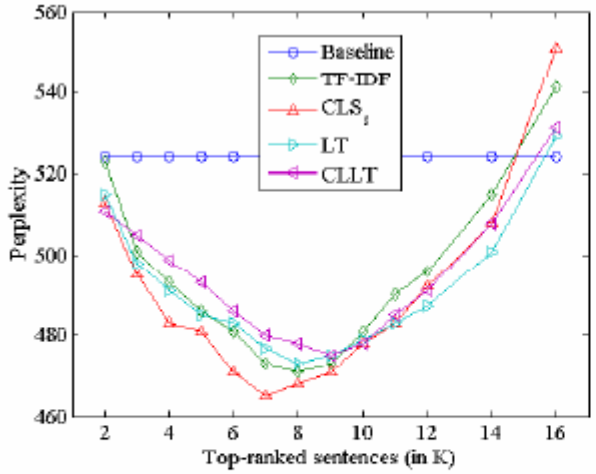
(a) interation number



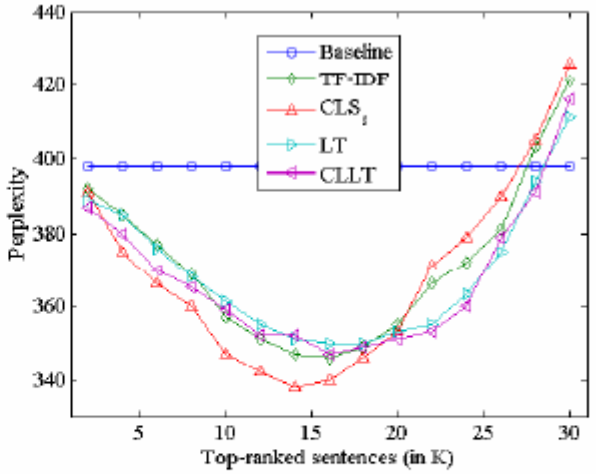
(b) topic number

Fig. 1: Perplexity vs. the number of different iterations and topics on two LM training corpus.

Perplexity Analysis



(a) IWSLT-07



(b) NIST-06

Fig. 2: English reference translation based perplexity of adapted LMs vs. the size of selected data on two test sets.

Perplexity Analysis

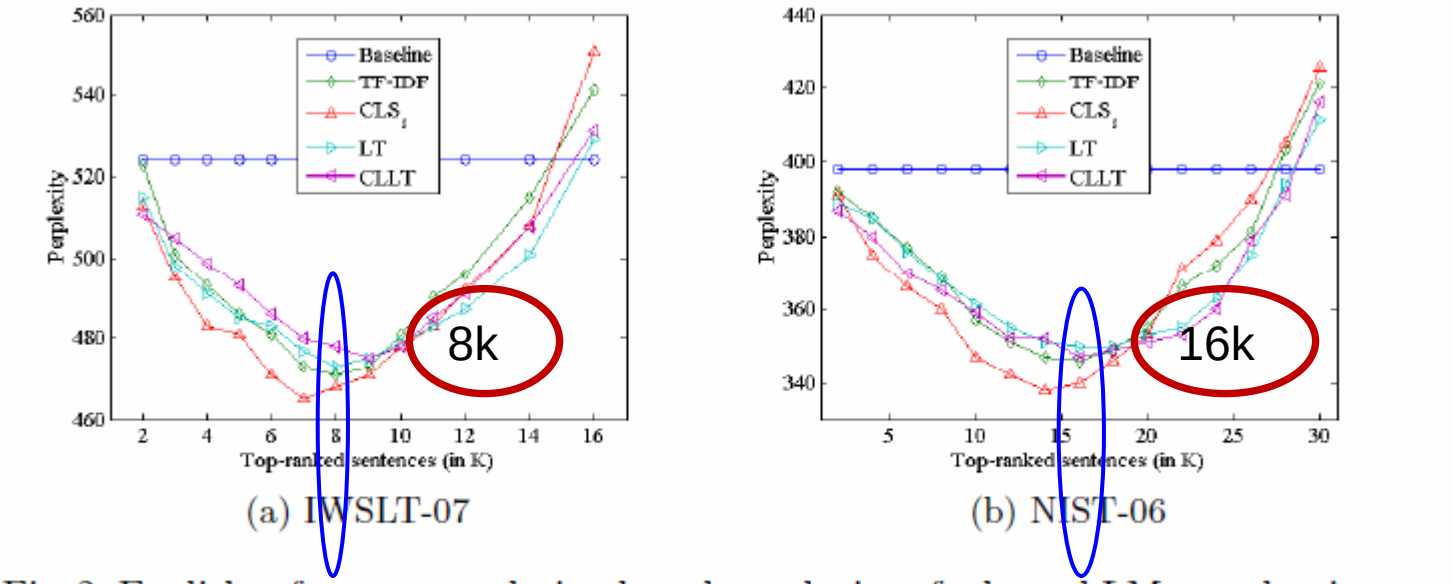


Fig. 2: English reference translation based perplexity of adapted LMs vs. the size of selected data on two test sets.

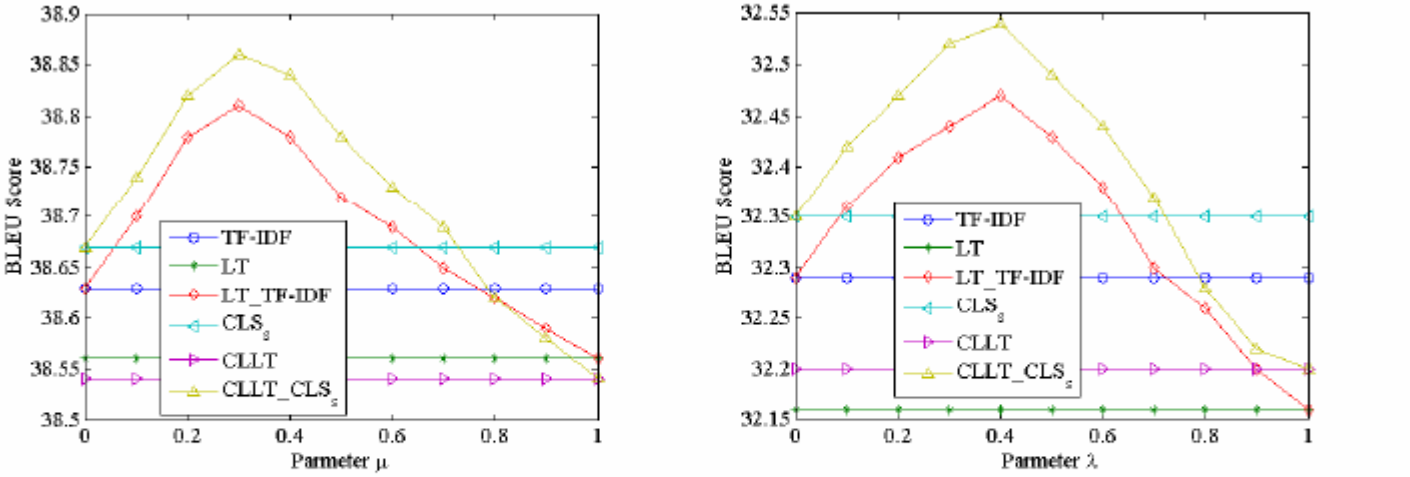
- IWSLT-07 : top 8K sentences
- NIST-06: top 16K sentences

Translation Experiments

- Tune parameter

$$P_{LT\_TF-IDF}(s|S) = \mu P_{LT}(s|S) + (1-\mu) P_{TF-IDF}(s|S)$$

$$P_{CLLT\_CLS_s}(\hat{s}|S) = \lambda P_{CLLT}(\hat{s}|S) + (1-\lambda) P_{CLS_s}(\hat{s}|S)$$



(a) IWSLT-07 (b) NIST-06

Fig. 3: The impact of parameters μ and λ to SMT performance on two development sets.

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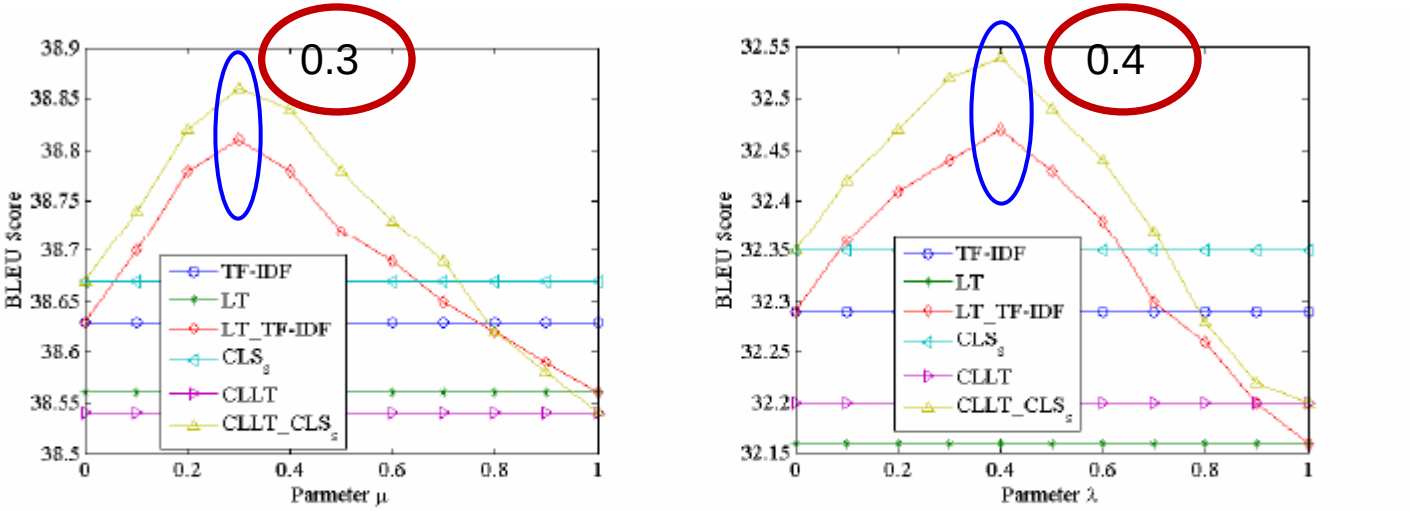

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Translation Experiments

Table 1: SMT performance with different data selection models for LM adaptation on two test sets.

Method	#	BLEU	
		IWSLT-07	NIST-06
Baseline	1	33.60	29.15
TF-IDF	2	34.14	29.78
CLS	3	34.08	29.73
CLS_s	4	34.18	29.84
LT	5	34.07	29.65
CLLT	6	34.05	29.69
LT_TF-IDF	7	**34.32**	**29.96**
CLLT_CLS_s	8	**34.37**	**30.03**

- CLSs performs better than CLS
  - **The added smoothing measure which makes similarity computation more accurate**

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- LT and CLLT do not outperform the baseline method TF-IDF

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- LT_TF-IDF significantly outperforms LT and TF-IDF
  - **The word-topic and word-distribution information is complementary to TF-IDF**

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- CLLT_CLSs outperforms LT TF-IDF, and CLSs outperforms TF-IDF
  - **first pass translation hypotheses have lots of noisy data**
  - **cross-lingual data selection model can avoid this problem**

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Conclusion

- **Word-topic and word-distribution information is very useful for data selection based LM adaptation**
- **Word-topic information is complementary to traditional approach**

Thanks !

Any questions?