Cross-Lingual Sentiment Classification Based on Denoising Autoencoder

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Outline

- Introduction
- Denoising Autoencoder (DAE)
- The Combination CLSC Approach Based on Denoising Autoencoder
- Experiments and Analysis
- Conclusion and Future Work

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- **Introduction**
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Sentiment Classification

- Sentiment classification technique is the task of predicting sentiment polarity for a given text
- Generally, sentiment classification approaches can be divided into two categories:
  - **Lexicon based approach**
  - **Machine learning based approach**

Cross-Lingual Sentiment Classification

- **Labeled data are very imbalanced**
  - The lack of sentiment resources limits the research progress in some languages.
- **Cross-Lingual Sentiment Classification (CLSC).**
  - leverage resources on one language (**source language**) to resource-poor language (**target language**) for improving the classification performance on target language

Problems

- The problems to be settled in CLSC task:
  - Machine translation services adopted in CLSC task, bring translation errors in training process
  - The language gap between source language and target language also influences the performance of system

Decrease the effects of noisy examples

- **To reduce the effect of translation errors**
  - Denoising autoencoder is adopted

- **To eliminate the language gap**
  - **Two classifiers** are trained in **English view** and **Chinese view** respectively, and the final results are combined from two classification outputs

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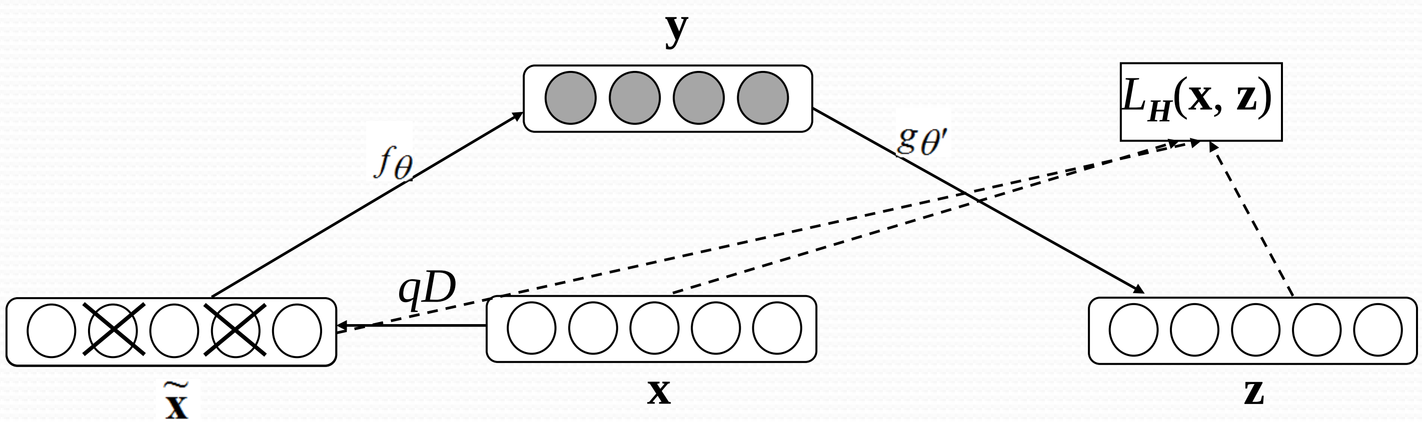
Autoencoder

Denoising Autoencoder



$$L_H(\mathbf{x},\mathbf{z}) = H(B_{\mathbf{x}} \parallel B_{\mathbf{z}}) = -\sum_{k=1}^{d}[\mathbf{x}_k \log \mathbf{z}_k + (1-\mathbf{x}_k)\log(1-\mathbf{z}_k)]$$

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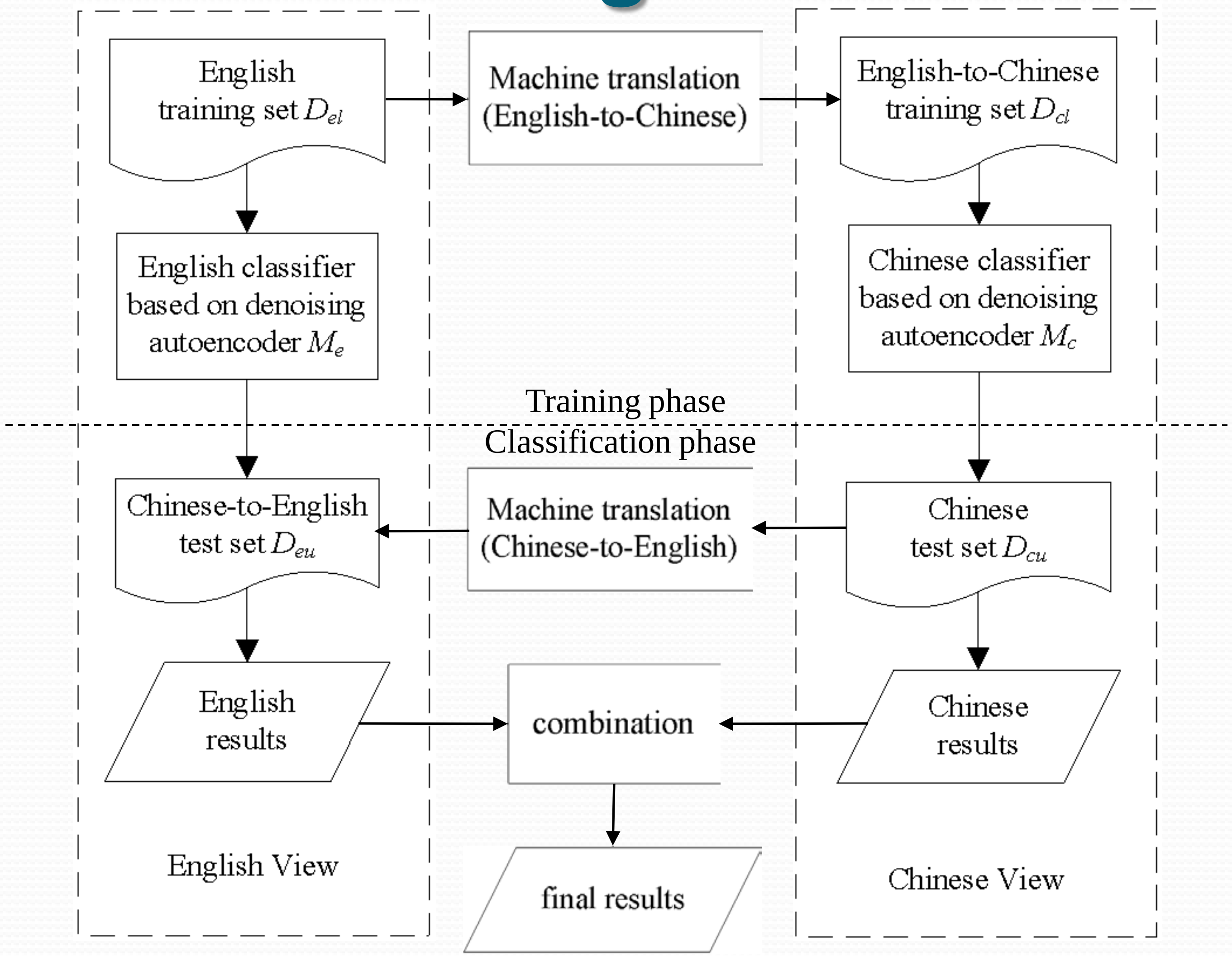
The Combination CLSC Approach Based on Denoising Autoencoder



The Advantages of This Approach

- Denoising autoencoder is adopted to reduce the impacts of training errors

- Training classifiers in **multi-views** helps to bridge the gap between English and Chinese

Feature Setting

- Sentiment Word Features Selection
  - High-Frequency Words Method
  - CHI Statistical Method

$$\chi^2(t_i, C_j) = \frac{N \times (A \times D - B \times C)^2}{(A+C) \times (B+D) \times (A+B) \times (C+D)}$$

- A: (t_i, C_i) B: $(t_i, \overline{C}_i)$
- C: $(\bar{t}_i, C_i)$ D: $(\bar{t}_i, \overline{C}_i)$

Feature Setting

- Negation Features

$$vector = (neg_1, sent_1, \ldots, neg_i, sent_i, \ldots, neg_{2000}, sent_{2000})$$

- Feature Weight Calculation
  - Boolean Method
  - Word Frequency Method
  - TF-IDF method

$$w_{ij} = tf_{ij} \times \log \frac{N}{n_i}$$

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Experimental Settings

- Dataset
  - NLP&CC 2013 cross-lingual sentiment classification dataset, including book, DVD and music categories
- Evaluation method
  - category accuracy
  - average accuracy

$$Accuracy_c = \frac{\#system\_correct}{4000}$$

$$Accuracy = \frac{1}{3}\sum_{i=1}^{3} Accuracy_c$$

- Model parameters
  - architecture: 4000-500-2
  - epoch: 30
  - learning rate: 0.1

Effect of Sentiment Word Features Selection

Table 1. Effect of Sentiment Word Features Selection

System	Methods	Book	DVD	Music	Accuracy
English	High-frequency	**74.53%**	75.43%	73.8%	74.58%
	CHI statistic	73.03%	**76.93%**	**75.15%**	**75.04 %** **(+0.46%)**
Chinese	High-frequency	**78.40%**	74.45%	73.15%	75.33%
	CHI statistic	78.15%	**75.05%**	**74.30%**	**75.83 %** **(+0.50%)**

Effect of Negation Features

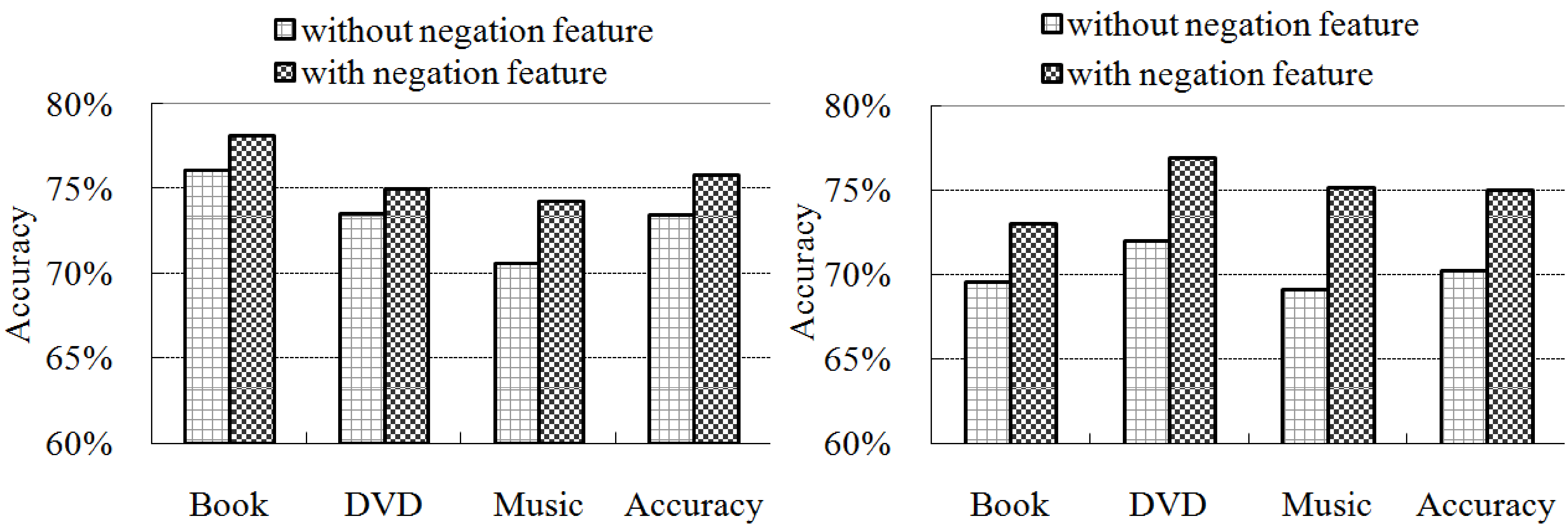

Fig. 3. Performance comparison with or without negation features

Effect of Feature Weight Calculation Methods

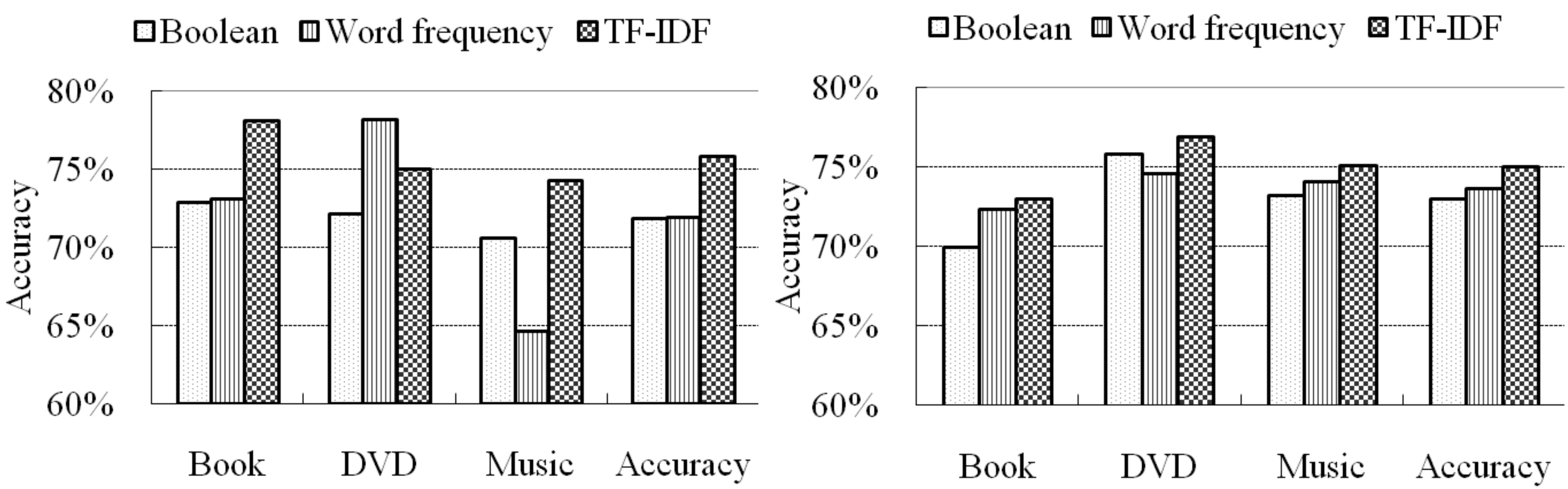

Fig. 4. Performance comparison with different weight calculation methods

Performance of Combination CLSC Systems

Table 2. Performance of combination CLSC systems

System	Book	DVD	Music	Accuracy
English system	73.03%	76.93%	75.15%	75.04%
Chinese system	78.15%	75.05%	74.30%	75.83%
Combination system	**79.68%**	**78.33%**	**78.08%**	**78.70%**

Effect of Destruction Fraction in Denoising Autoencoders

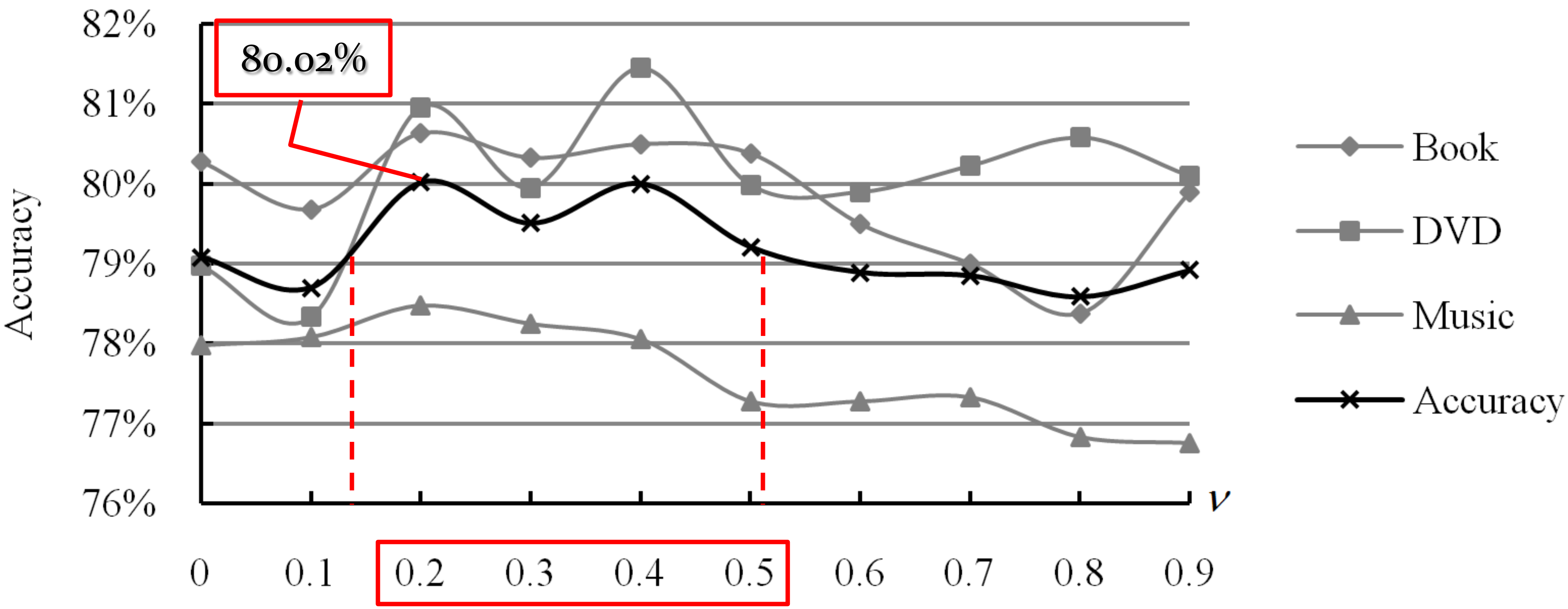

Fig. 5. Accuracy vs. Destruction fraction

Comparison with Related Work

Table 3. CLSC performance comparison on the NLP&CC 2013 Share Task test data

Team	Book	DVD	Music	Accuracy
Chen et al. 2014	77.00%	78.33%	75.95%	77.09%
HLT-Hitsz	78.50%	77.73%	75.13%	77.12%
Gui et al. 2013	78.70%	79.65%	78.30%	78.89%
Our Approach	**80.63%**	**80.95%**	**78.48%**	**80.02%**

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Conclusion

- Denoising autoencoder and combination approach could improve the sentiment classification performance.
  - decrease the impacts of translation errors
  - eliminate the language gap
- The feature setting of CHI feature selection method together with TF-IDF weight calculation method works well on CLSC task.

Future Work

- Deep combination of classifiers rather than linear combination only
  - Such as co-training or transfer learning strategy

- Select high-quality translated reviews for training Chinese classifier to further reduce the impacts of translation errors.

Thank you!