

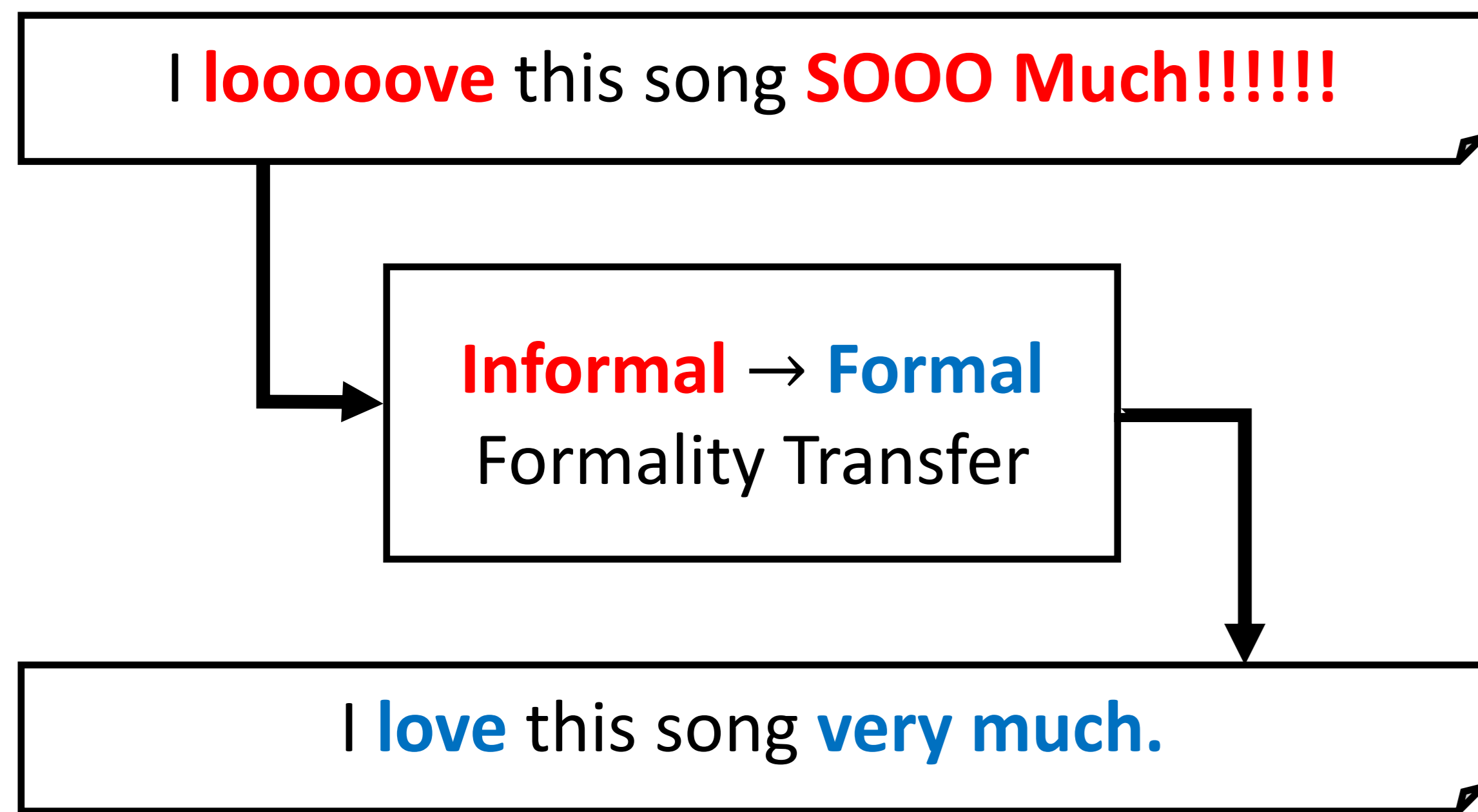
# Edit Distance Based Curriculum Learning for Paraphrase Generation

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## Paraphrase Generation

- Can be formulated as a monolingual machine translation problem
- Application examples
  - English education support
  - Preprocessing for machine translation



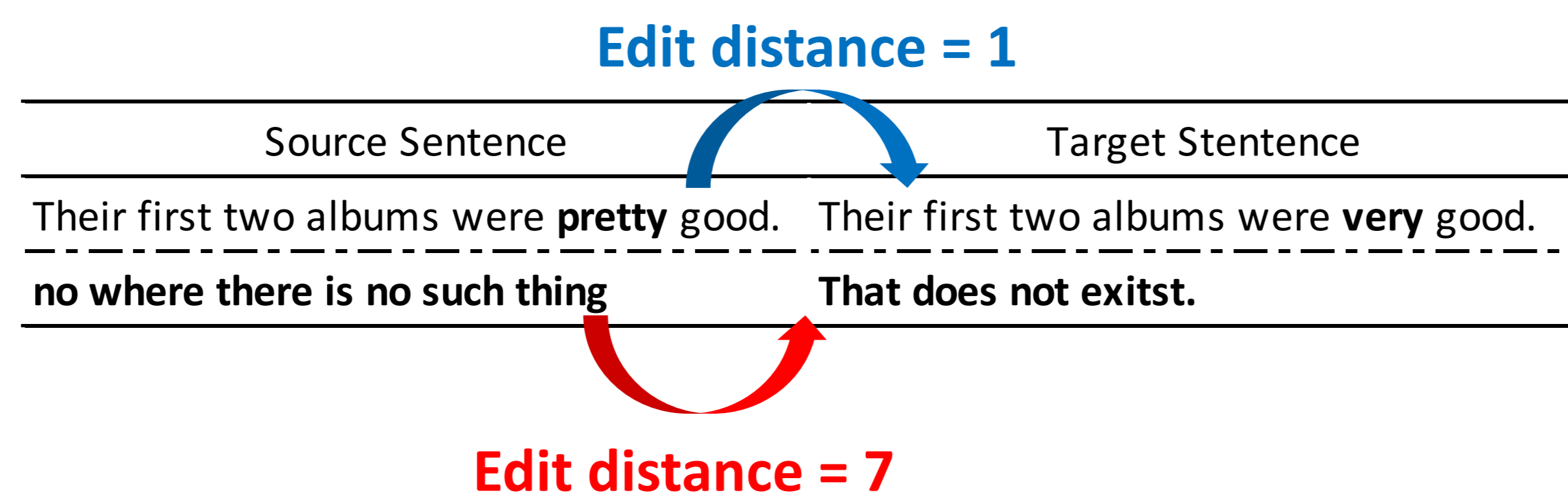
## Difficulty of Paraphrase Generation

- Paraphrases require a few transformations: Copy almost all the input sentence's words (**Easy**)
- Paraphrases require drastic transformations: Require complex rewriting operations (**Difficult**)
- We propose to estimate the difficulty of transformations by **edit distance**

Source Sentence	Target Sentence
Their first two albums were <b>pretty</b> good.	Their first two albums were <b>very</b> good.
no where there is no such thing	That does not exist.

## Edit Distance

- Number of edit operations required to convert the word sequence
- Small edit distance: **Easy**
- Large edit distance: **Difficult**



## Proposed Method

### Edit Distance Based Curriculum Learning

- Apply curriculum learning to paraphrase generation
- Use the existing curriculum learning framework [1]
- The metric of difficulty
  - Edit Distance (ED)

## Experiment on Formality Transfer

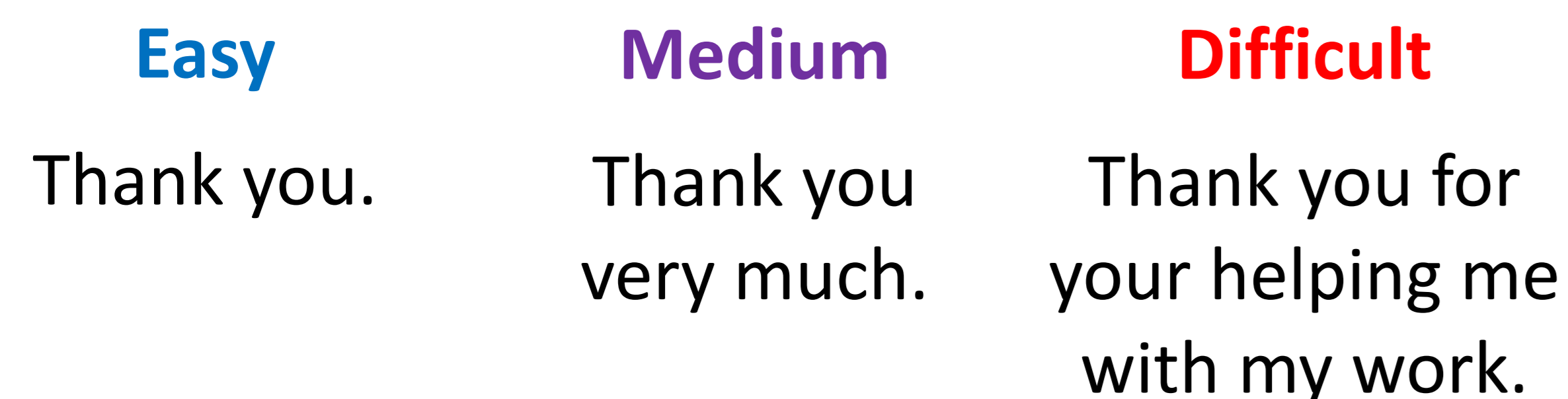
### Evaluate the quality of paraphrase generation

- Setup
  - Dataset: GY AFC [2]
  - Model: Transformer
  - Evaluation metric: BLEU
- Comparison methods
  - Baseline: Without curriculum learning
  - CL-SL: Curriculum learning with sentence length
  - CL-WR : Curriculum learning with word rarity
  - CL-ED : Curriculum learning with edit distance

	Informal → Formal	
	E&M	F&R
Source	49.19	50.94
Baseline	69.81	75.02
CL-SL	69.83	74.90
CL-WR	70.05	74.62
CL-ED	<b>70.34</b>	<b>75.41</b>

## Curriculum Learning

- Training a model starting from easy samples and gradually moving to difficult ones
- Curriculum learning for machine translation [1]
  - Improve translation quality
  - The metric of difficulty
    - Sentence Length (SL)
    - Word Rarity (WR)

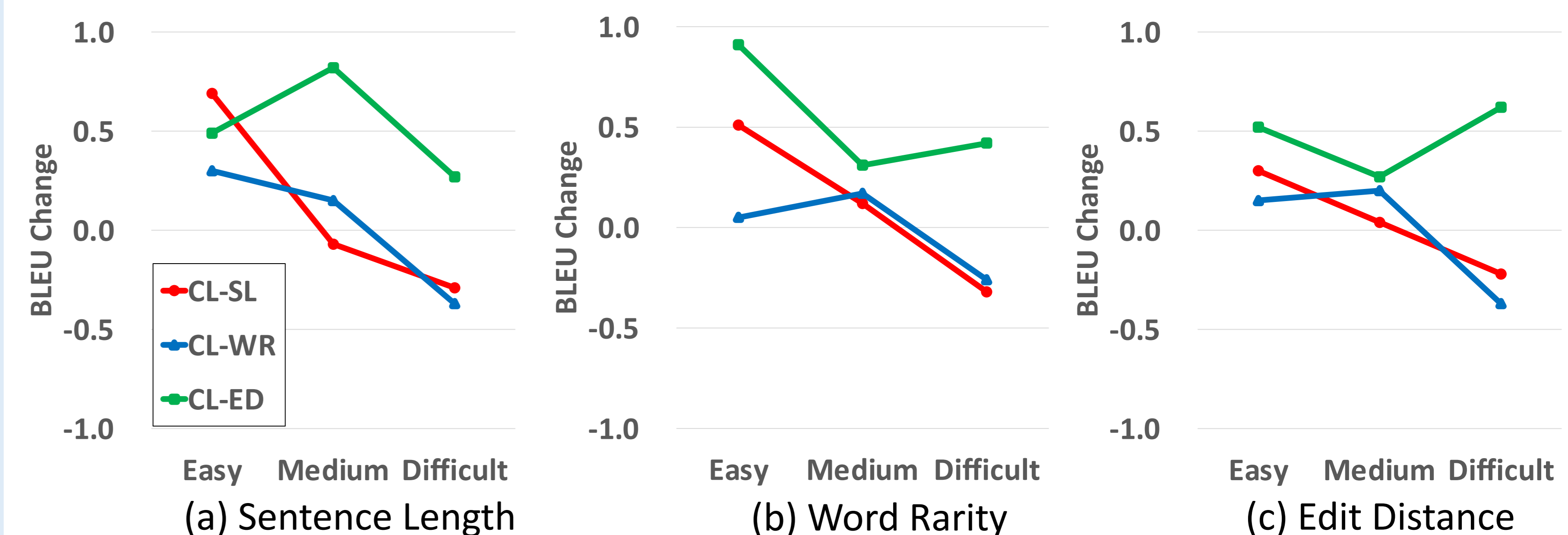


Training Time

## Analysis

### Investigate which types of sentences are improved

- Procedures
  - Divide the test set based on difficulty levels
  - Compute a BLEU score of each class
  - Calculate improvements over Baseline
- Results
  - CL-SL and CL-WR degraded the quality of difficult samples
  - CL-ED improved the quality of all classes regardless of difficulty levels



[1] Platanios et al. (NAACL 19) Competence-based Curriculum Learning for Neural Machine Translation

[2] Rao and Tetreault (NAACL 18) Dear Sir or Madam, May I Introduce the GY AFC Dataset: Corpus, Benchmarks and Metrics for Formality Style Transfer