A Hybrid Text Normalization System using Multi-head Self-attention for Mandarin

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How can this paper be helpful?

Can it only be applied to Mandarin?

- Nope.

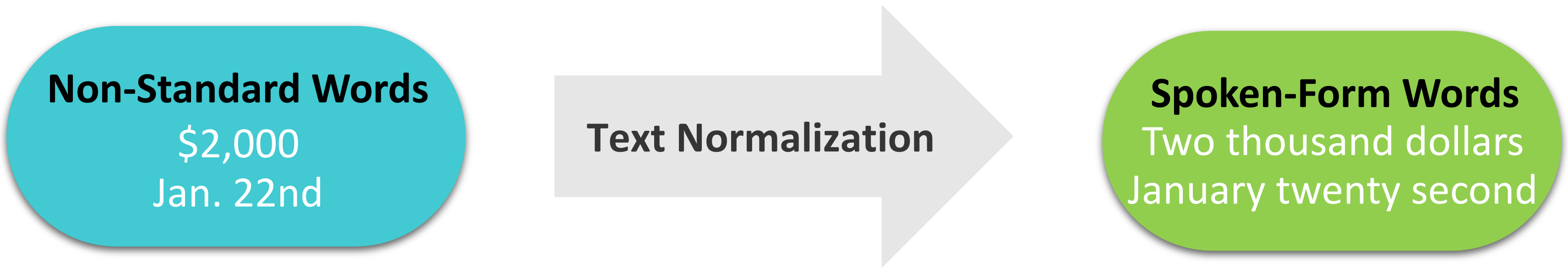
To what languages could it be helpful?

- Any language with a rule-based Text Normalization system.

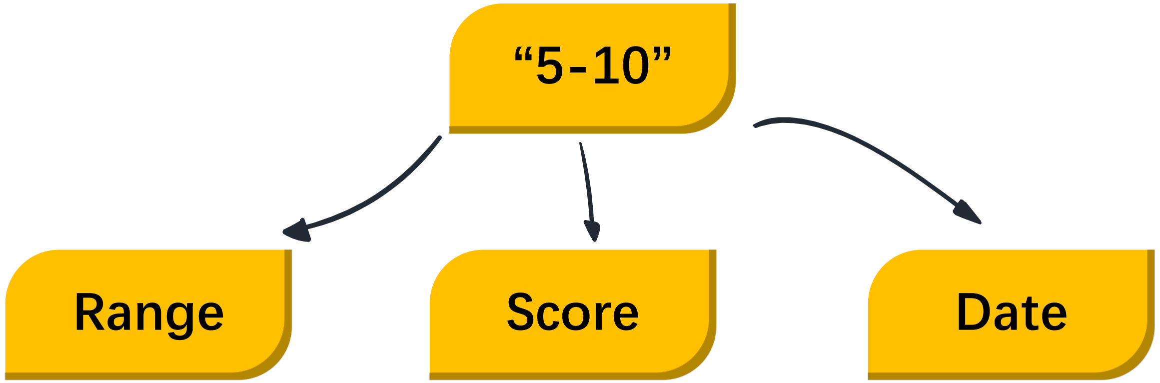
Goal for this paper?

- Improve the performance of a rule-based model.
- Combine system flexibility and model generalizability.

Text Normalization (TN)



Challenge: Ambiguous Cases



Rule-based TN System

Match non-standard words with rules

- Regular Expressions
- Keywords
- Priority

Pros:

- Flexible (add new rules easily)
- Highly developed (handle various cases)

Cons:

- Hard to improve on general cases

Neural TN Model

Classification Neural model

- Carefully designed pattern groups
- Multi-head self-attention

Table 1. Examples of some dataset pattern rules.

Pattern Name	Pattern Example
A_Read_No_Zero	200 people
A_Spell_Keep_Zero	The 2020 Conference
B_Percent	Only 10% of students voted
B_Range	about 10-15 degree
B_Score_Ratio	Team A is 30-10 leading
B_Slash_Per	There are five people/group
B_Time	It starts at 10:30
B_Date_YMD	Today is 2019-10-01
A_Two_Liang	2个人 (2 people)
A_One_Yao_Spell	打911 (Call 911)

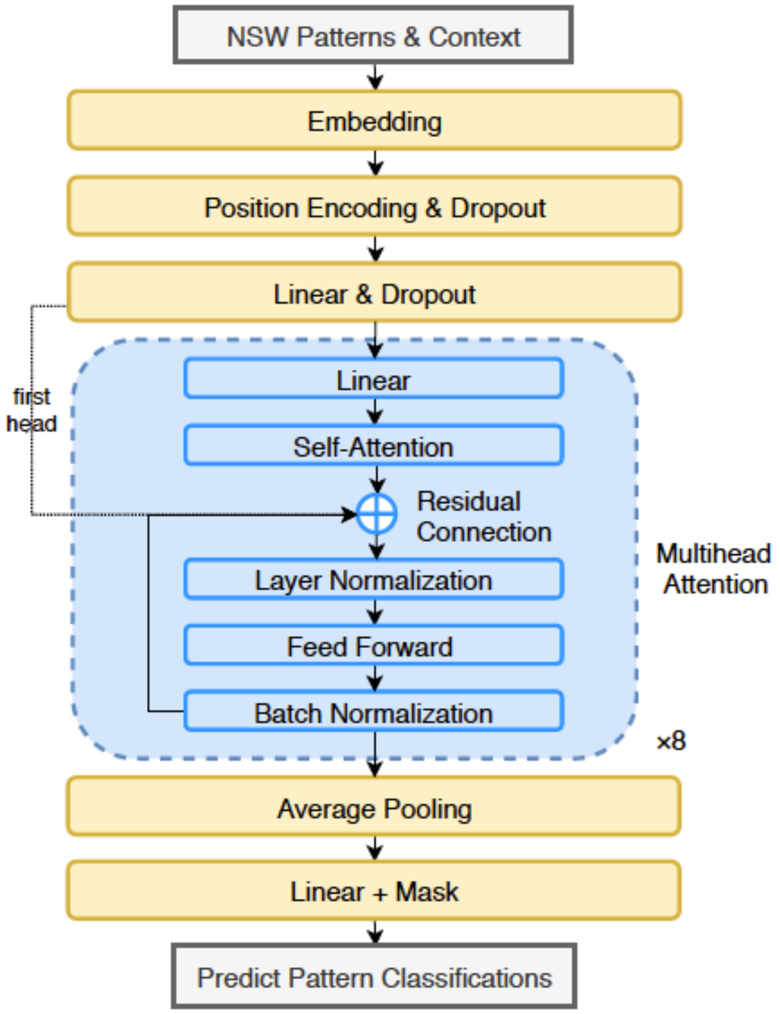


Fig. 2. Multi-head self-attention model structure.

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Neural TN Model

Word Embedding

- A pretrained Word2Vec model on Wikipedia text.
- Finetune on a pre-trained BERT model.

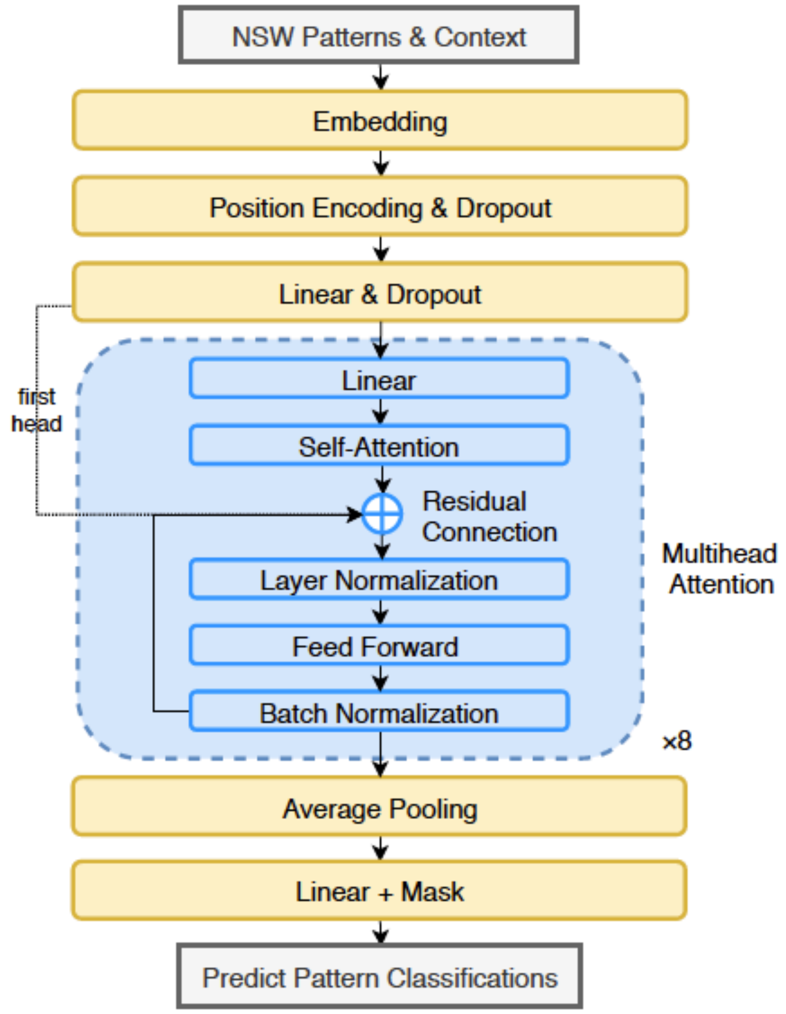

Fig. 2. Multi-head self-attention model structure.

Proposed Hybrid System

- Priority Check (rule-based TN model)
  - Easy to add user-defined strings.
  - Easy to add special cases (e.g. 911).
  - Handles 22.8% non-standard words.
- Main Module (neural TN model)
  - Handles 77.2% non-standard words.
- Pattern Check (rule-based TN model)
  - 2.2% failed patterns from the main module.
  - Normalization of all remaining patterns.

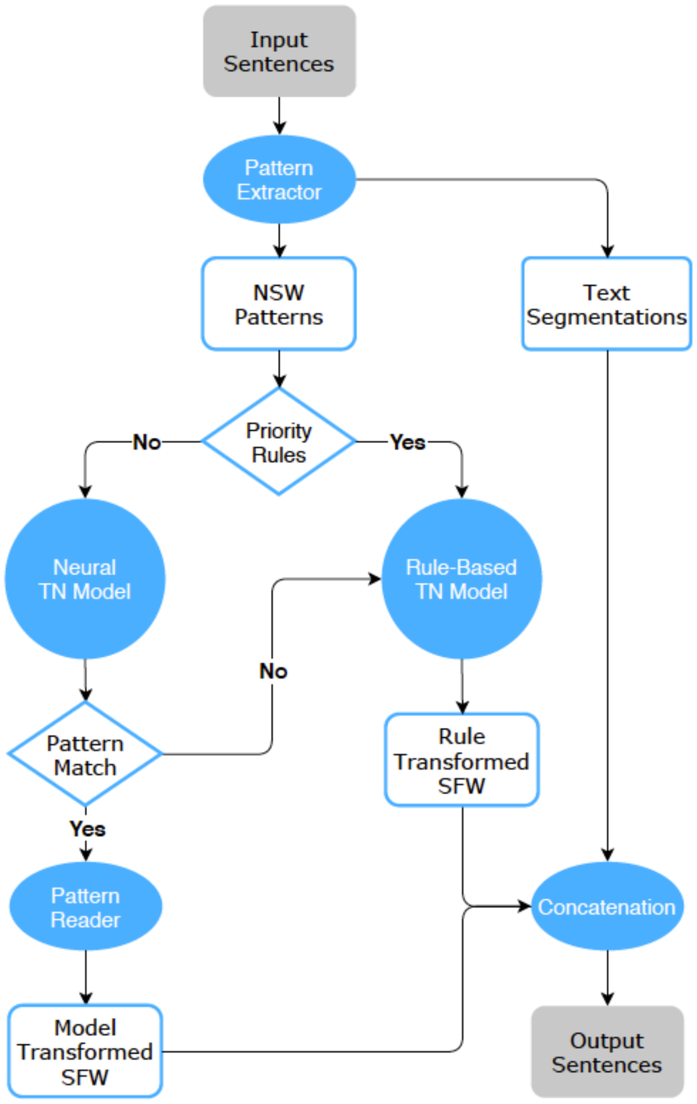

Fig. 1. Flowchart of the proposed hybrid TN system.

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Another Challenge – Imbalanced Dataset

- The dataset is imbalanced
  - Top 5 patterns take up > 90%.
  - Leading to a less robust neural model.
- Solutions
  - Introduce focal loss.

$$L = \begin{cases} -\alpha_t (1-p)^{\gamma} \log(p), \text{if} & y = 1 \\ -\alpha_t p^{\gamma} \log(1-p), \text{if} & y = 0 \end{cases} \quad (1)$$

  - Data expansion.
    - Data duplication, context replacing, random digits change…

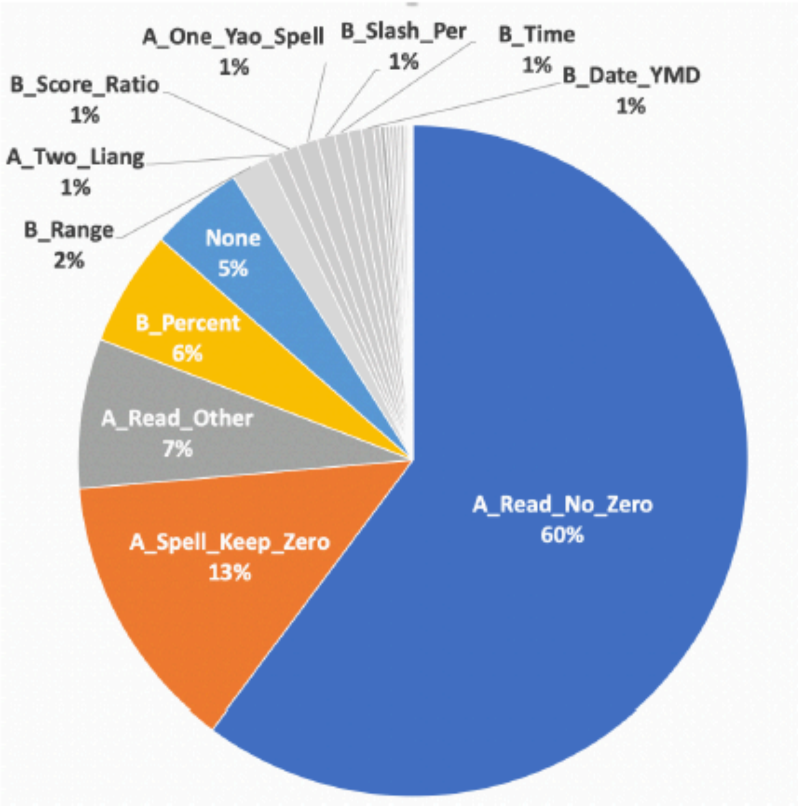

Fig. 3. Label distribution for dataset.

Experimental Result – Neural Model

- Proposed system has the following configurations:
  - Word2Vec Word Embedding.
  - Focal Loss without data expansion.
  - Bi-classification mask (whether a symbol exists).

Table 2. Comparison of different experimental setups.

Experimental setup	Accuracy
Model 1 (proposed)	0.916
Model 2 (+ BERT)	0.904
Model 3 (+ pad 0's)	0.914
Model 4 (+ max window)	0.907
Model 5 (+ CE loss)	0.913
Model 6 (- mask)	0.910
Model 7 (+ data expansion)	0.908

Experimental Result – Neural Model

- Neural model performance on different pattern groups.

Table 3. Model performance on the test dataset.

Pattern Name	Precision	Recall	F_1
A_Read_No_Zero	0.974	0.979	0.977
A_Spell_Keep_Zero	0.932	0.916	0.924
B_Percent	0.998	0.990	0.994
B_Range	0.932	0.932	0.932
B_Time	0.969	0.912	0.939
B_Score_Ratio	0.962	0.962	0.962
B_Slash_Per	0.994	0.966	0.980
B_Date_YMD	1.000	0.923	0.960
A_Two_Liang	0.613	0.797	0.693
A_One_Yao_Spell	0.637	0.631	0.634
Overall Accuracy		0.916	

Experimental Result – Proposed System

- Performance comparison on golden test set (~70,000 sentences)
  - Increased accuracy by 1.9% on sentence level.
  - On average, 95.5% pattern accuracy is achieved.
  - Our service shows the system is more robust on different types of news.

Table 4. Model performance on the news golden set.

	Sentence Accuracy	Pattern Accuracy
Rule-based TN model	0.867	0.946
Proposed TN system	0.886	0.955

Thanks for watching!