



Correcting Chinese Word Usage Errors for Learning Chinese as a Second Language

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Abstract

With more and more people around the world learning Chinese as a second language, the need of Chinese error correction tools is increasing. In the HSK dynamic composition corpus, **word usage error (WUE)** is the **most common** error type. In this paper, we build a neural network model that **considers both target erroneous token and context** to generate a correction vector and compare it against a candidate vocabulary to propose suitable corrections. To deal with potential alternative corrections, the top five proposed candidates are judged by native Chinese speakers. For **more than 91%** of the cases, our system can propose **at least one acceptable correction within a list of five candidates**. To the best of our knowledge, this is the **first research** addressing **general-type Chinese WUE correction**. Our system can help non-native Chinese learners revise their sentences by themselves.

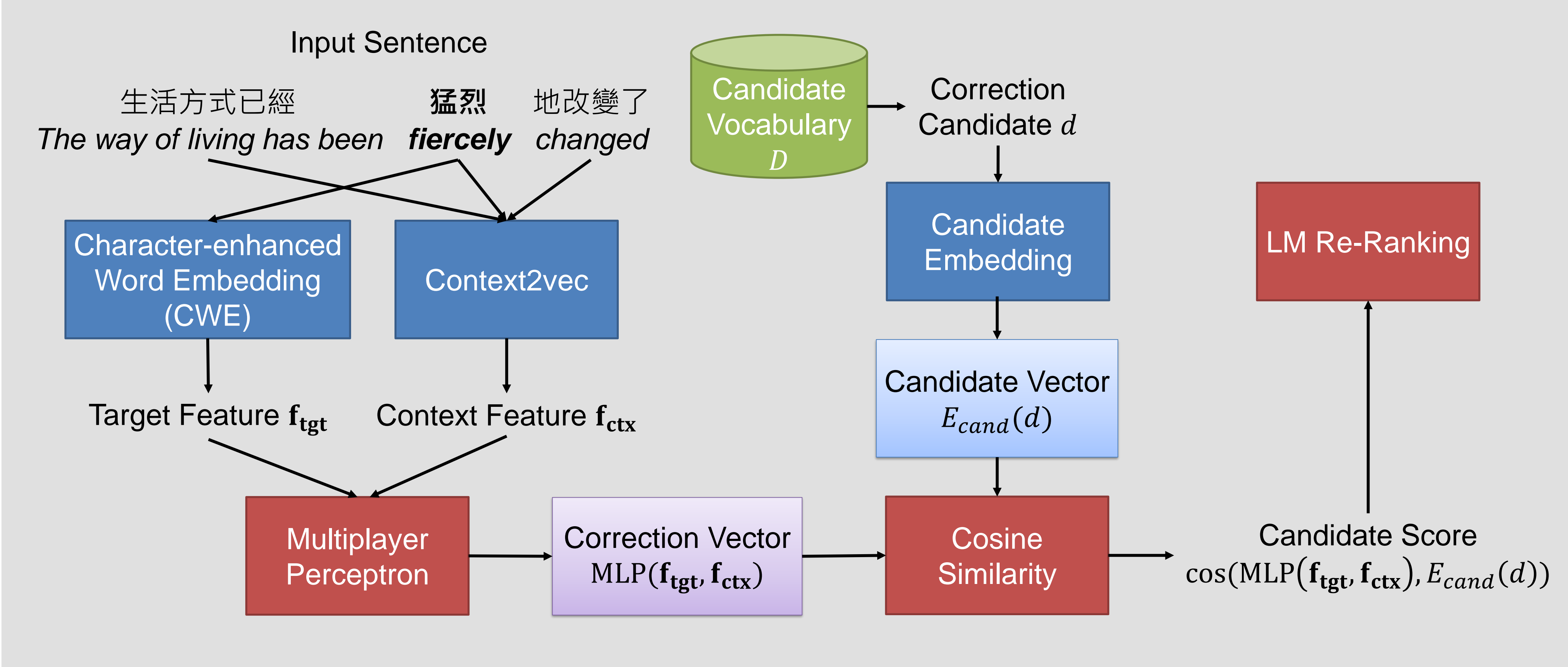
Introduction

- **Chinese word usage error (WUE):** incorrect token involving morphological, syntactical, or semantical problems
- Incorrect word form e.g. *決解 ju'e ji'e
- Correct existent word that is improper for its context
- **Goal:** given a known erroneous token in a sentence segment → generate suitable correction
- **Criteria for suitable correction**
 1. **Correctness (C):** result is syntactically and semantically correct
 2. **Similarity (S):** meaning close to writer's intended meaning

	C	S
*生活方式已經 猛烈 地改變了 (The way of living has been fiercely changed.)		
*生活方式已經 暴烈 地改變了 (... has been overpoweringly changed.)	X	O
生活方式已經 緩慢 地改變了 (... has been slowly changed.)	O	X
生活方式已經 劇烈 地改變了 (... has been dramatically changed.)	O	O

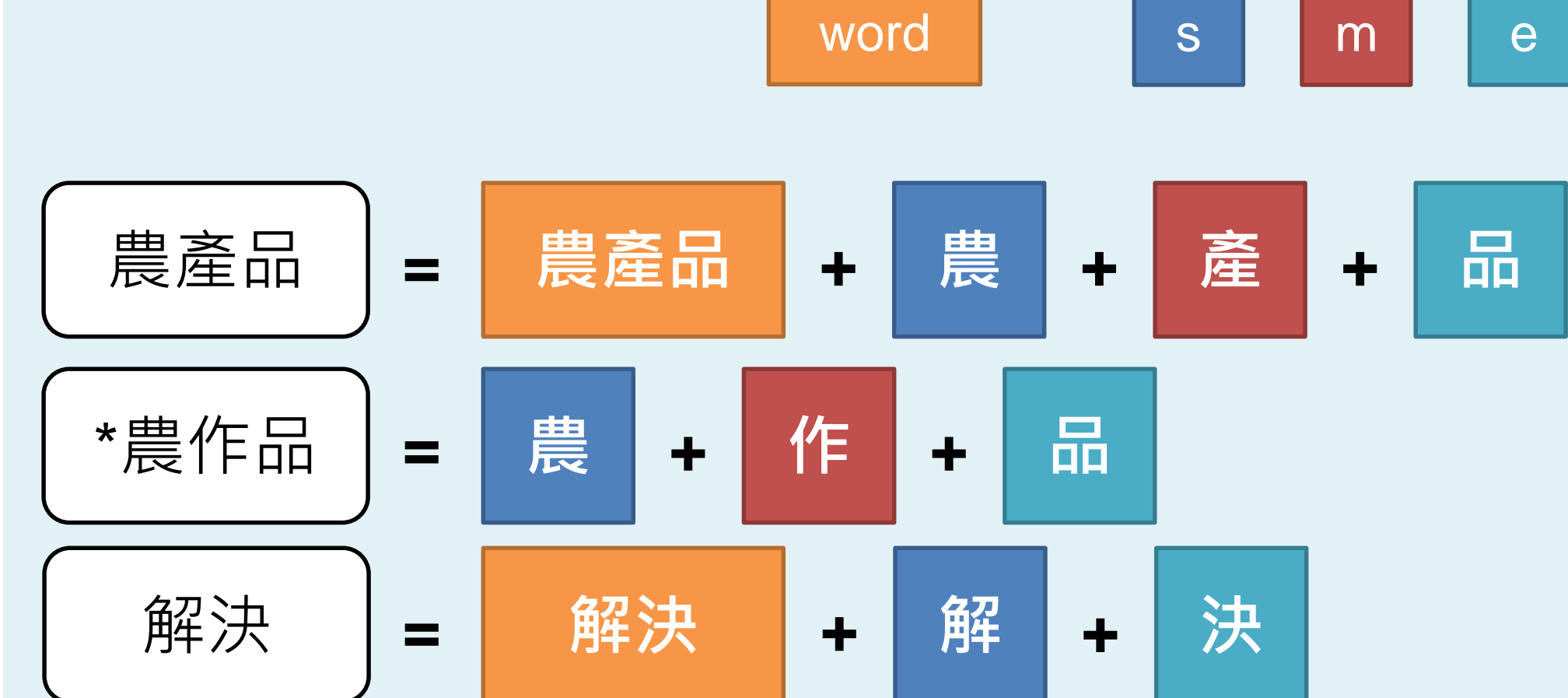
- **C > S:** incorrect sentence can confuse language learner!
- **Main contributions**
 1. First study to correct all types of WUEs
 2. Human evaluation → at least one acceptable correction within top five candidates for more than 91% cases
 3. HSK WUE dataset with additional human annotations

Neural Network-based Correction Generation Model

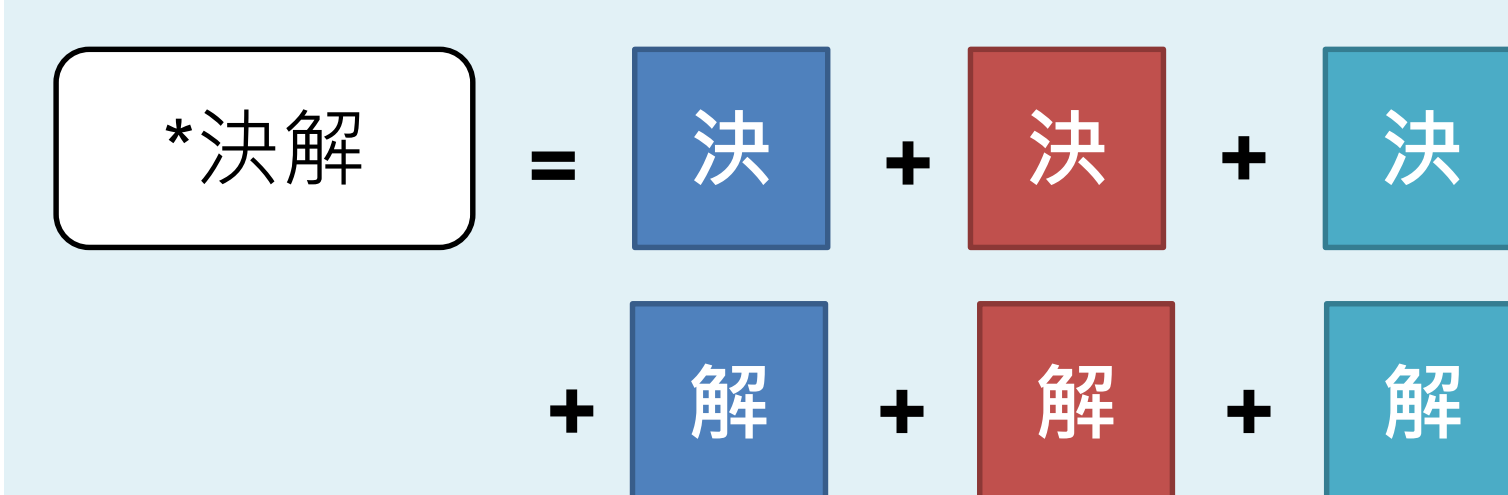


Input Features

Target CWE+P Word Embedding (CWE_w)



CWE Position-Insensitive Character Embedding (CWE_c)



Context2vec Features → $C2V_{tgt}$

- 可是每個人的[境況]都千差萬別
- $C2V_{ctx} = \text{LSTM}(\text{可是每個人的}) \oplus \text{LSTM}(\text{千差萬別都})$

POS Features

- 70% POS unchanged after correction
- Systematic changes e.g. NN ↔ VV
- One-hot encoding as input features

LM Re-ranking

	C	S
*到山頂之間路走得不容易 (The road between the hilltop was not easy to walk.)		
*到山頂 期間 路走得不容易 (The road period the hilltop ...)	X	O
到山頂的 路 走得不容易 (The road to the hilltop ...)	O	O

- Model sometimes generates candidates that seriously violate correctness criterion
 - LM probability reflects the level of correctness
- $$r_{com} = \frac{1}{\frac{\alpha}{r_{LM}} + \frac{1-\alpha}{r_{DNN}}}$$
- r_{com} can be interpreted as rank, smaller better

Evaluation

Target features	Context features	Acc.	MRR	Hit@5
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Baselines (No training on the WUE dataset)

-	N-gram LM	0.1659	0.2438	0.3268
-	RNNLM	0.1468	0.2208	0.2847
-	$C2V_{ctx}$	0.0714	0.1170	0.1575

Correction Generation Model – C2V

$C2V_{tgt}$	-	0.2507	0.3030	0.3561
-	$C2V_{ctx}$	0.1249	0.1746	0.2273
$C2V_{tgt}$	$C2V_{ctx}$	0.3249	0.3891	0.4566

Correction Generation Model – CWE + Others

CWE_w		0.2898	0.3545	0.4195
+ CWE_c		0.2946	0.3570	0.4234
+ $C2V_{tgt}$	+ $C2V_{ctx}$	0.3512	0.4250	0.5024
+ POS		0.3717	0.4378	0.5063

Effect of LM Re-ranking

Model	Acc.	MRR	Hit@5	Hit@10
Best MLP	0.3717	0.4378	0.5063	0.5688
+ N-gram LM	0.3727	0.4605	0.5561	0.6439
+ RNNLM	0.3727	0.4527	0.5278	0.6205

Human Evaluation

Evaluation	Acc.	MRR	Hit@5	Hit@10
Ground-truth	0.3727	0.4605	0.5561	0.6439
+ Annotation	0.6829	0.7784	0.9122	0.9171

Performance on most frequent POS tags

POS (#)	Acc.	MRR	Hit@5	Mean rank
VV (316)	0.67	0.77	0.91	26.12
NN (277)	0.64	0.73	0.88	73.97
AD (130)	0.65	0.75	0.88	96.16
P (62)	0.81	0.88	0.95	3.10
VA (45)	0.60	0.76	0.98	1.98
DEV (23)	1.00	1.00	1.00	1.00
PN (21)	0.71	0.80	0.95	2.33

Conclusion

- MLP correction generation model considers both target & context
- Apply LM re-ranking to emphasize correctness
- Future work: phonetical similarity e.g. (影響 yǐng xiǎng, 印象 yìn xiàng)