

# Correcting Pronoun Homophones with Subtle Semantics in Chinese Speech Recognition

Zhaobo Zhang, Rui Gan, Pingpeng Yuan, Hai Jin

National Engineering Research Center for Big Data Technology and System
Service Computing Technology and System Laboratory
Cluster and Grid Computing Laboratory
Huazhong University of Science and Technology, Wuhan, China

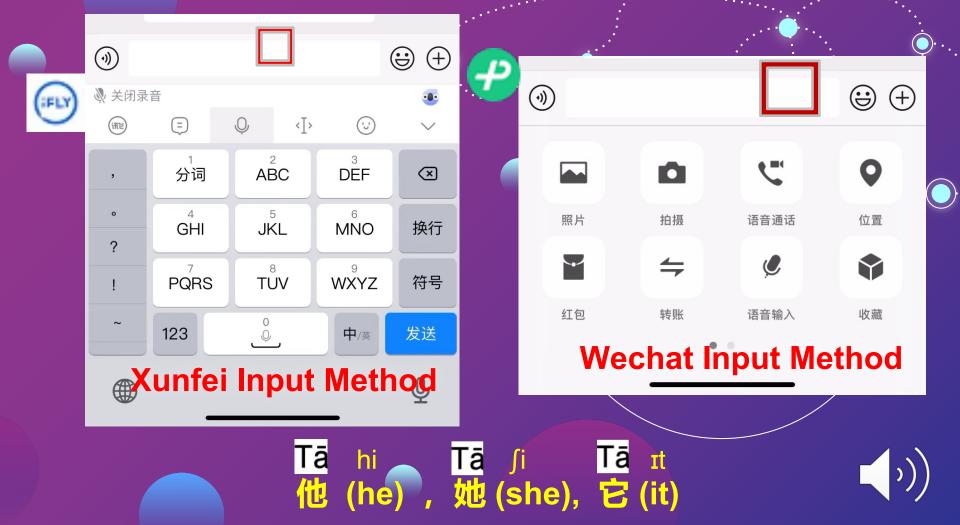


LREC-COLING 2024

# **OUTLINES**

Motivation	"Ta" classification in Chinese Speech Recognition			
Solution	"Ta Correct" scheme & TaR/TaL/TaN Model			
Evaluation	luation Comparison with Baselines & Experimental Results			
Conclusion	Summary of Findings & Next Steps			
Q&A Session				





#### **Cause**

- English third-person pronouns (he/she/it) differ in pronunciation.
- Chinese third-person pronouns (他/她/它) share pronunciation.
- Chinese pronouns references are more ambiguous
- Void Reference "Ta" in Modern Chinese

#### **Realted Work**

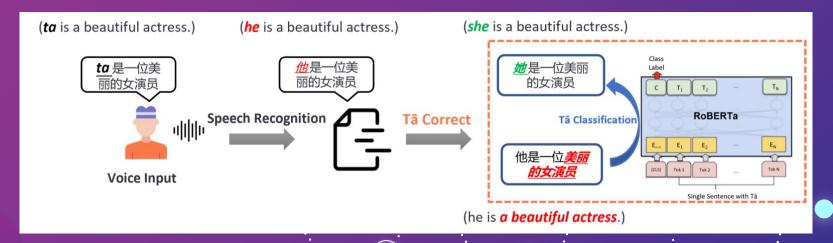
- Chinese spelling correction (CSC). Most errors arise from homophones.
- Deep neural networks like RNN and LSTM for audio-to-text processing
- End-to-end structure with pre-trained BERT to differentiate phonetics and characters

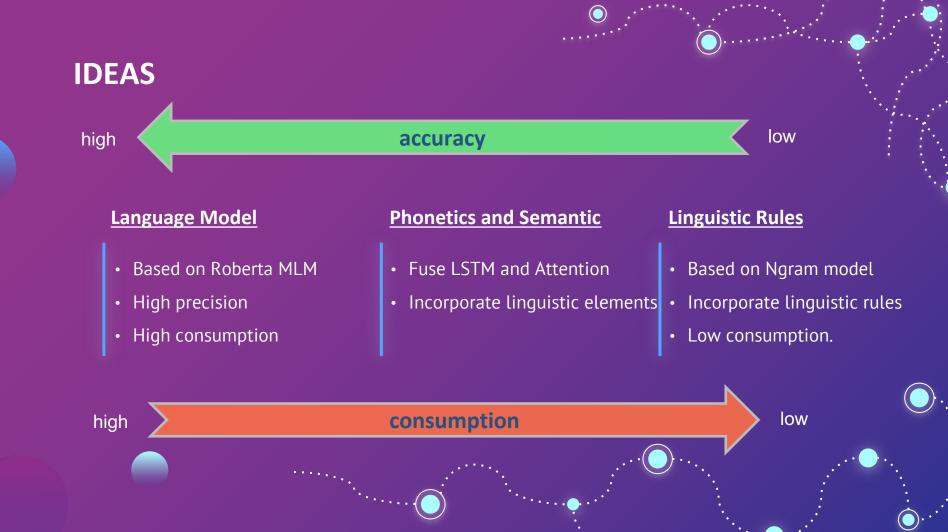


### **IDEAS**

Inspired by Chinese spelling correction, propose the post-processing "Ta Correct" scheme

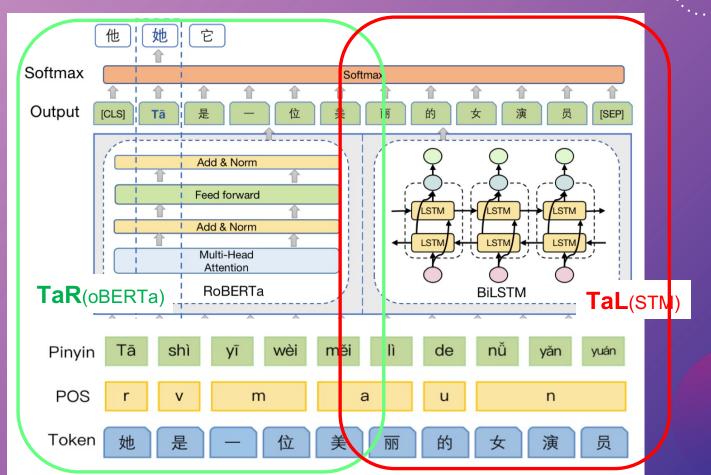
- Language model
- > LSTM model with phonetics and semantic features
- Rule-based assisted Ngram model





#### **METHODOLOGY** Trm Trm . . . Trm Trm Trm . . . E<sub>Wuqi</sub> $\mathsf{E}_{\mathsf{Dynamic}}$ E<sub>County</sub> E<sub>[CLS]</sub> E<sub>changes</sub> E<sub>soil</sub> E<sub>erosion</sub> E<sub>[SEP]</sub> $E_A$ $E_A$ $E_B$ $E_B$ [MASK] [SEP] [SEP]

# Language Model / LSTM Model



### LSTM + Attention

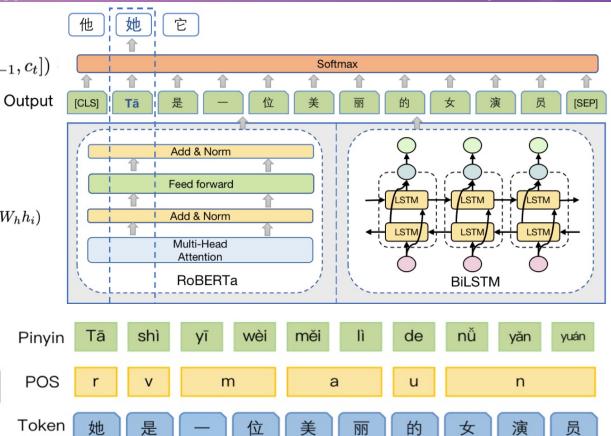
$$y_t = g(s_{t-1}, c_t) = \operatorname{softmax}(W_o[s_{t-1}, c_t])$$

$$c_t = \sum_i a_{t,i} h_i$$

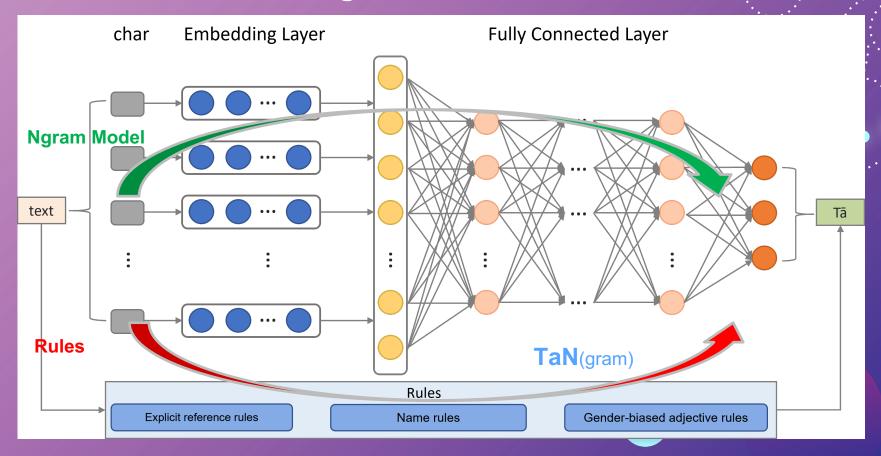
$$e_{t,i} = extit{align}(s_{t-1}, h_i) = V^T anh(W_s s_{t-1} + W_h h_i)$$
  $a_{t,i} = extit{Softmax}(e_{t,i}) = rac{\exp(e_{t,i})}{\sum_j \exp(e_{t,j})}$ 

$$h_t = \textit{BiLSTM}(x_t)$$

$$x_t = \left[x_t^{text}; x_t^{pos}; x_t^{pinyin}\right]$$



# **Rule-based Assisted Ngram Model**



### Rules

Explicit reference rules: words or characters that explicitly distinguish "他" (he), "她" (she), and "它" (it), such as "男" (male) for "他" (he), "女" (female) for "她" (she), and "兔 子" (rabbit) for "它" (it).

Name rules: commonly used characters in male and female names. For example, "强" (strong) is commonly found in male names, while "丽" (beautiful) frequently appears in female names.

Gender-biased Adjective Rules: adjectives with gender bias also carry implicit meanings. Word like "漂亮" (beautiful) often describes "她" (she), while "英俊" (handsome) commonly describes "他" (he).



### 1. Experimental Settings

#### **Datasets**

- Weibo: Sourced from the Sina Weibo, totaling over 360,000 sentences, of which 57,384 sentences contain "Ta".
- Smp: It consists of Weibo data covering various topics related to the COVID-19, with 5,000 sentences, of which 3,020 sentences contain "Ta".
- Tieba: Derived from forum posts, over 2,320,000 sentences, of which 946,969 sentences contain "Ta".

We generate speech data for these sentences using machine-generated pronunciation. We divide the train and test set in 7:3 ratio.

# 1. Experimental Settings

#### **Baselines**

- Open-source speech recognition models: including PaddleSpeech and Whisper
- Commercial input methods: including Baidu Speech Recognition and Xunfei
   Automatic Speech Recognition.

### 1. Experimental Settings

#### **Evaluation Metrics**

- In-Sentence Accuracy (ISA): The average of the accuracy of the predicted Ta in each sentence, reflecting how accurately the model identifies "Ta" on a sentenceby-sentence basis
- Whole Sentence Accuracy (WSA): Proportion of sentences in which the prediction
   Ta is all accurate, indicating the model's effectiveness at perfect prediction across entire sentences
- "Ta" Conversion Accuracy (TCA): Prediction accuracy of Ta for the entire dataset,
   assessing the model's comprehensive performance in correctly identifying "Ta."

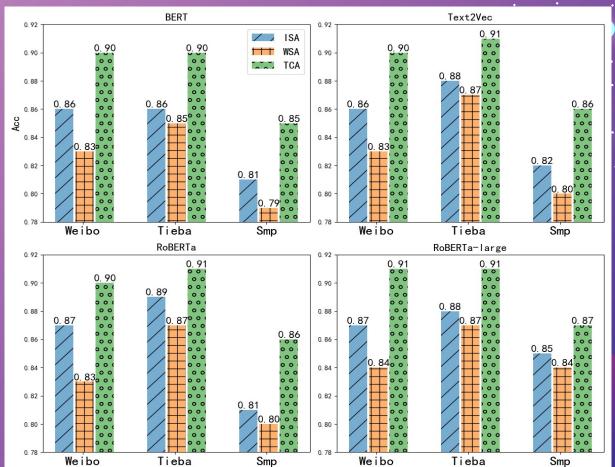
# 2. Experimental Results

Model	el Weibo		Tieba			Smp			
l l	ISA	WSA	TCA	ISA	WSA	TCA	ISA	WSA	TCA
Paddle + $\emptyset$	0.66	0.59	0.66	0.82	0.76	0.80	0.70	0.63	0.66
+ TaR	0.87 ↑ o.	21 0.84 ↑ 0.2	5 0.90 ↑ 0.24	0.87 ↑ 0.05	<b>0.85</b> † 0.09	0.90 ↑ 0.10	0.85 ↑ 0.15	0.84 ↑ 0.21	0.88 ↑ 0.22
+ TaL	0.80 ↑ 0.	14 0.76 ↑ 0.1	7 <b>0.84</b> † 0.18	0.81 \$\psi\$ -0.0	1 <b>0.80</b> † 0.04	0.86 ↑ 0.06	0.75 ↑ 0.05	0.72 ↑ 0.09	0.80 ↑ 0.14
+ TaN	0.78 ↑ 0.	12 0.73 ↑ 0.1	4 <b>0.81</b> ↑ 0.15	0.81 \ -0.0	1 0.76 -	0.82 ↑ 0.02	0.73 ↑ 0.03	0.67 ↑ 0.04	0.73 ↑ 0.07
Whisper + ∅	0.69	0.62	0.67	0.81	0.78	0.82	0.71	0.66	0.78
+ TaR	0.87 ↑ 0.	18 <b>0.83</b> † 0.2	1 0.90 ↑ 0.23	0.87 ↑ 0.06	<b>0.85</b> † 0.07	0.90 ↑ 0.08	0.82 ↑ 0.11	0.79 ↑ 0.13	0.85 ↑ 0.07
+ TaL	0.78 1 0.	09 0.73 ↑ 0.1	1 <b>0.82</b> † 0.15	0.81 -	0.80 ↑ 0.02	0.86 ↑ 0.04	0.75 ↑ 0.04	0.73 ↑ 0.07	0.81 ↑ 0.03
+ TaN	<b>0.75</b> ↑ o.	06 <b>0.71</b> † 0.0	9 <b>0.81</b> ↑ 0.14	0.80 \$\\$\tag{0.00}\$	1 0.74 \ -0.04	0.81 \ -0.01	0.73 ↑ 0.02	0.68 ↑ 0.02	0.74 \ \ -0.04
Baidu + Ø	0.66	0.51	0.64	0.74	0.62	0.73	0.66	0.60	0.62
+ TaR	0.86 ↑ 0.	20 0.82 ↑ 0.3	1 0.89 ↑ 0.25	0.88 ↑ 0.14	0.86 ↑ 0.24	0.91 ↑ 0.18	0.82 ↑ 0.16	0.81 ↑ 0.21	0.86 ↑ 0.24
+ TaL	0.79 ↑ o.	13 <b>0.74</b> ↑ 0.2	3 <b>0.82</b> ↑ 0.18	0.82 ↑ 0.08	3 <b>0.80</b> † 0.18	0.86 ↑ 0.13	0.73 ↑ 0.07	0.70 ↑ 0.10	0.78 ↑ 0.16
+ TaN	<b>0.77</b> ↑ o.	11 0.73 ↑ 0.2	2 0.82 ↑ 0.18	0.81 ↑ 0.07	<b>0.75</b> ↑ 0.13	0.82 ↑ 0.09	0.71 ↑ 0.05	0.65 ↑ 0.05	0.72 ↑ 0.10
Xunfei + ∅	0.71	0.57	0.72	0.82	0.74	0.81	0.69	0.58	0.65
+ TaR	0.88 ↑ 0.	17 <b>0.84</b> ↑ 0.2	7 <b>0.91</b> 🕇 0.19	0.88 ↑ 0.06	6 <b>0.87</b> † 0.13	<b>0.91</b> ↑ 0.10	0.81 ↑ 0.12	0.79 ↑ 0.21	0.85 ↑ 0.20
+ TaL	0.81 ↑ 0.	10 0.77 ↑ 0.2	0 0.84 1 0.12	0.86 ↑ 0.04	<b>0.80</b> † 0.06	0.85 ↑ 0.04	0.72 ↑ 0.03	0.69 ↑ 0.11	0.78 ↑ 0.13
+ TaN	0.79 1 o.	08 0.75 1 0.1	B 0.86 1 0.14	0.80 \$\psi\$ -0.00	2 0.76 1 0.02	0.83 ↑ 0.02	0.72 1 0.03	0.65 ↑ 0.07	0.73 ↑ 0.08

## 3. Other Experiments

> Role of BERT Model

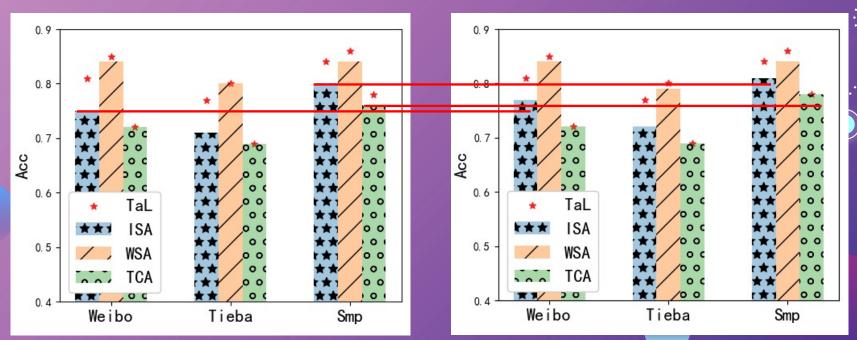
- ◆ BERT-base
- ◆ Text2vec
- ◆ RoBERTa
- ◆ RoBERTa-large √



## 3. Other Experiments

Role of Linguistic Features

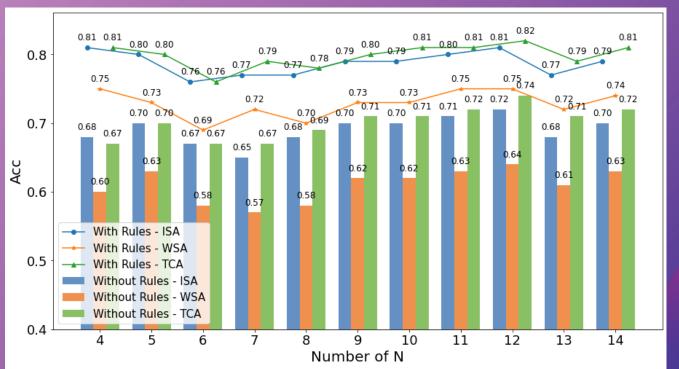
Pinyin plays a more prominent role than POS. It loses more accuracy on both ISA and TCA metrics.



## 3. Other Experiments

#### Effect of the N and Rules

As N increases, there is a trend where the performance decreases first and then increases again with the best results observed around N=12.



# 4. Case Study

Wanted Sentence	Recognized Sentence (Xunfei)	Corrected Sentence
她是一位美丽的女演员	他是一位美丽的女演员	她是一位美丽的女演员
She is a beautiful actress	He is a beautiful actress	She is a beautiful actress
妹妹最爱喝果汁,所以我为 <mark>她</mark> 留了一瓶 My sister loves juice best, so I saved a bottle for her	妹妹最爱喝果汁,所以我为 <mark>她</mark> 留了一瓶 My sister loves juice best, so I saved a bottle for her	妹妹最爱喝果汁,所以我为她留了一瓶 My sister loves juice best, so I saved a bottle for her
我养了一只小白兔,它最爱吃萝卜	我养了一只小白兔, <mark>他</mark> 最爱吃萝卜	我养了一只小白兔,它最爱吃萝卜
I raised a small white rabbit,	I raised a small white rabbit,	I raised a small white rabbit,
and it likes to eat radish	and he likes to eat radish	and it likes to eat radish



### **Conclusion and Future Works**

#### Contribution

 We've created three models, each with different costs, to handle different situations and better recognize the third-person pronoun "Ta" in speech-to-text applications.

#### **Future Works**

 We plan to explore additional rules and techniques for more pronouns to help advance Chinese spelling correction quickly.
 Our goal is to develop more adaptable models to enhance a wider array of applications and improve the user experience.





# THANKS!

### **DO YOU HAVE ANY QUESTIONS?**

zhang\_zb@hust.edu.cn



LREC-COLING 2024