The 2021 Conference on Empirical Methods in Natural Language Processing

SOM-NCSCM: An Efficient Neural Chinese Sentence Compression Model Enhanced with Self-Organizing Map

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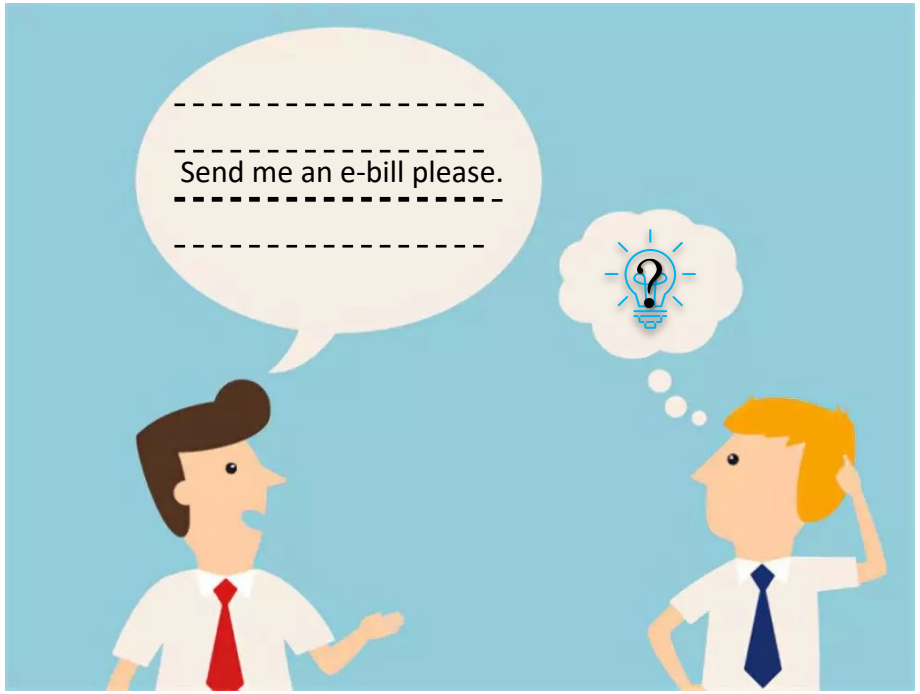
Outline

- Motivation
- Dataset
- Models
- Results

What is Sentence Compression (SC)?



- The **SC** aims to **shorten verbose sentences into concise ones**.
- Most approaches have treated it as a **deletion-based processing** and formalized it as a **sequence labeling problem**.
- The SC can benefit several real applications, such as automatic title generation (Zhang et al., 2012; Wang et al., 2018), information extraction, opinion mining (Feng et al., 2010), machine translation (Liet al., 2020), and question answering systems.

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Problems in Chinese Sentence Compression

1. Lacking corpora of Chinese parallel data which are necessary for training and evaluating Chinese SC models.
   - Translating the English SC corpora into Chinese, or collecting data from news websites.
   - But those data are mostly written in **Chinese formal expressions** and **not made publicly available** or exactly extraction-based.
2. High cost of annotating Chinese data.
3. Current Chinese SC approaches are more unsupervised-method-based.
   - Using heuristic rules ⟶ hard to be reused
   - Using statistical probabilities, like the TF-IDF ⟶ lack flexibility and capacity

Contributions

1. Lacking corpora of Chinese parallel data which are necessary for training and evaluating Chinese SC models.

1. A Chinese SC dataset
   - Chinese colloquial sentences from a real-life QA system in the telecommunication domain.

2. High cost of annotating Chinese data.

3. Current Chinese SC approaches are more unsupervised-method-based.
   - Using heuristic rules ⟶ hard to be reused
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Contributions

1. Lacking corpora of Chinese parallel data which are necessary for training and evaluating Chinese SC models.

1. A Chinese SC dataset
   - Chinese colloquial sentences from a real-life QA system in the telecommunication domain.

2. An entire neural Chinese SC model — SOM-NCSCM
   - Using a neural cluster method to enhance the performance of the neural Chinese SC model.

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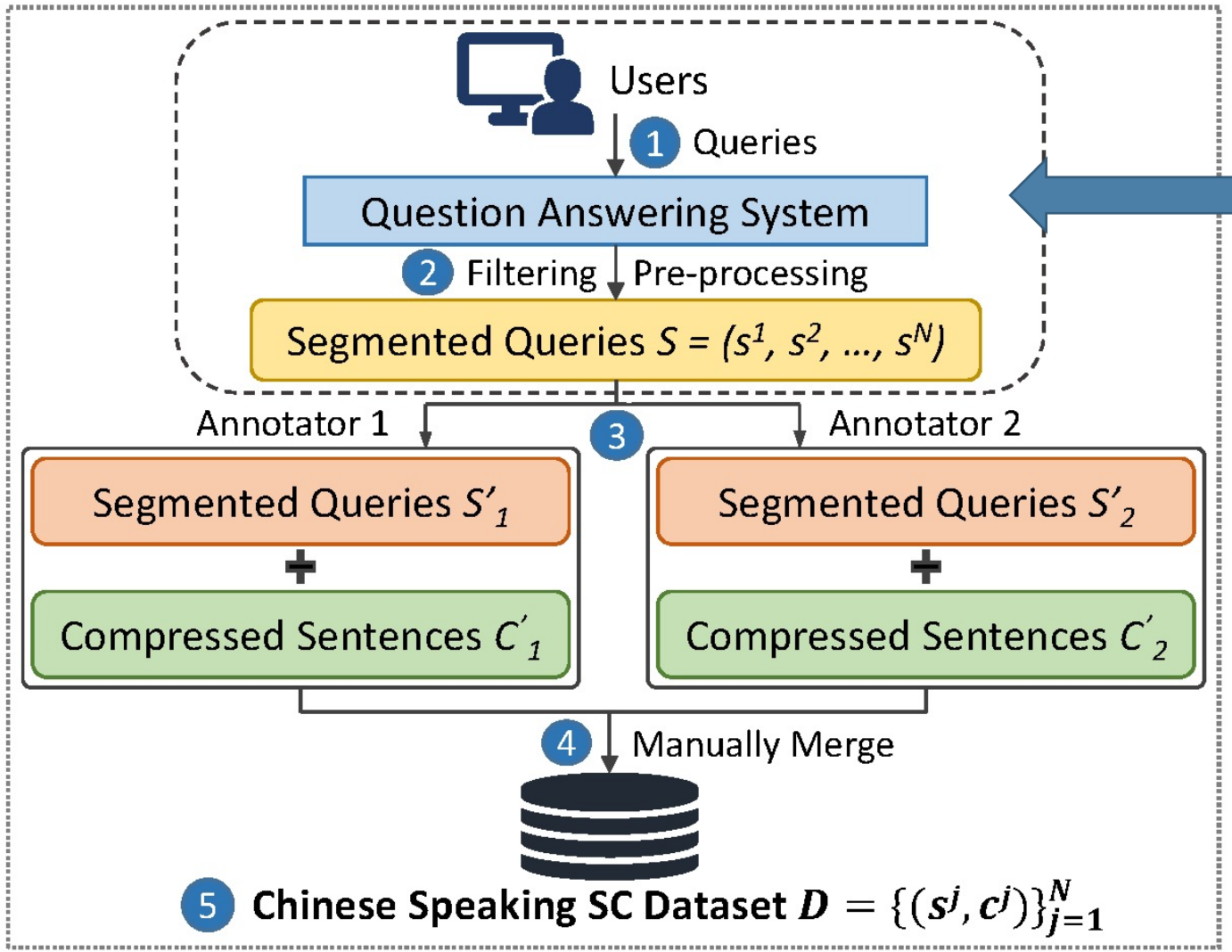
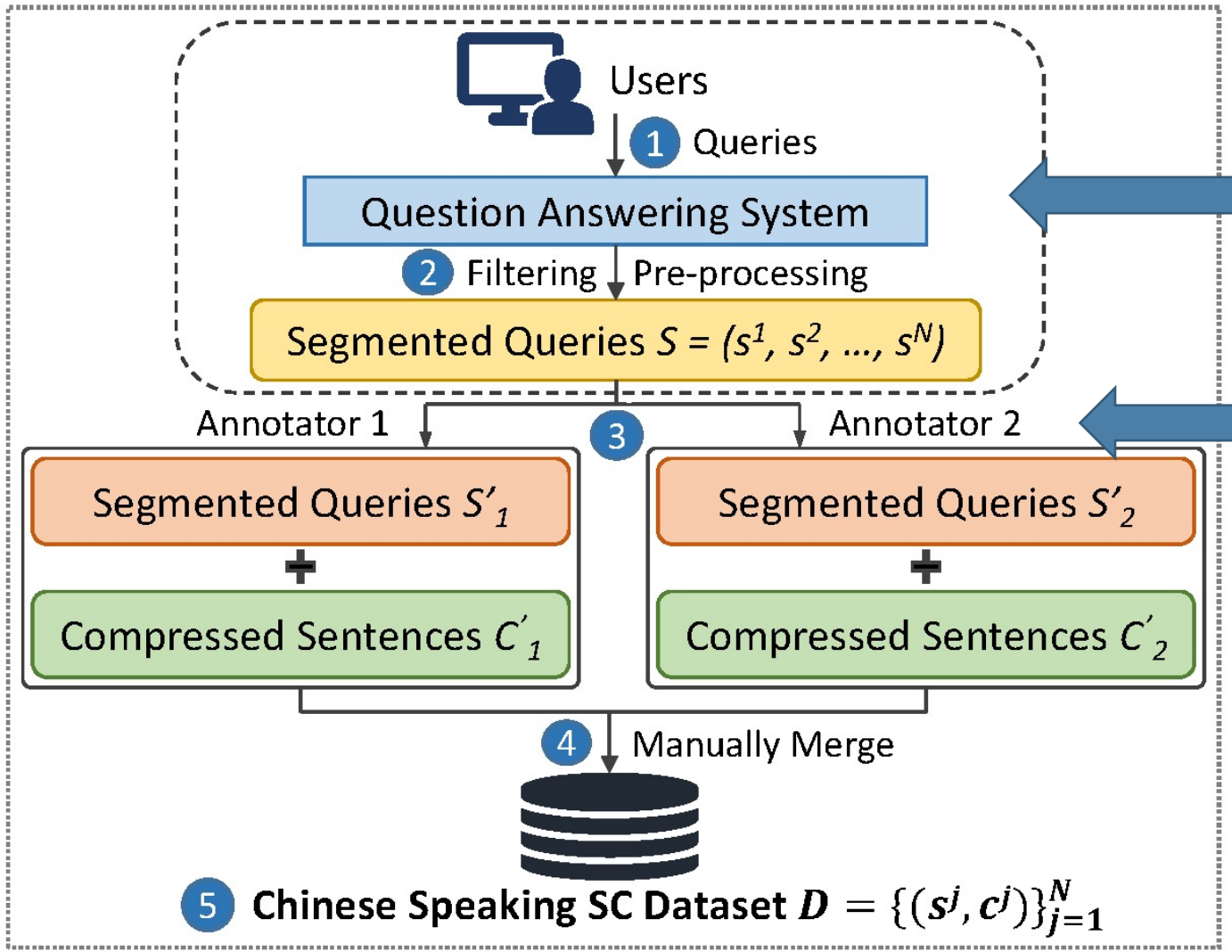
Data Collection and Annotation



✓ Data Source

Data Collection and Annotation



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✓ Data Annotation

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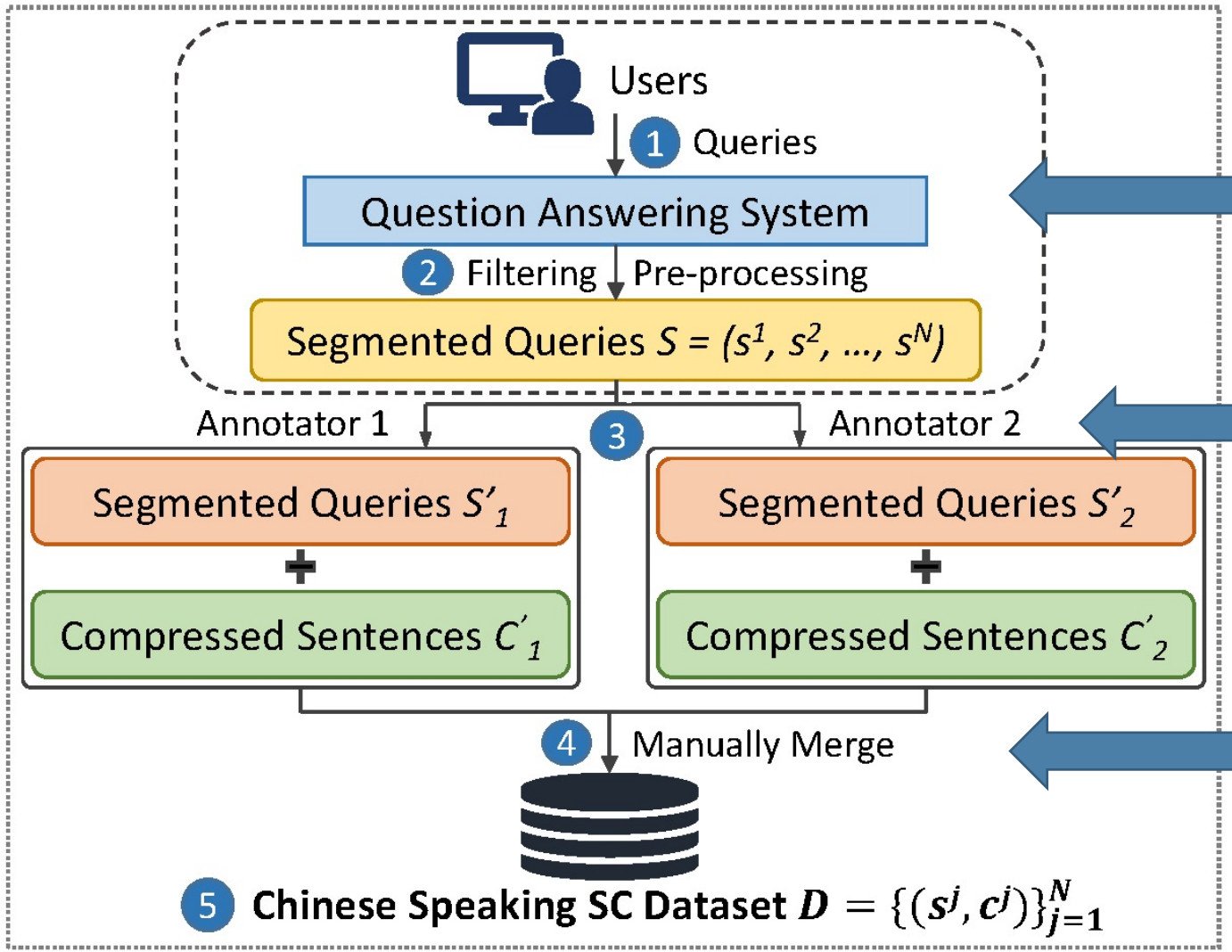

✓ Data Source

✓ Data Annotation

✓ Merge Data

Data Evaluation and Description

✓ Data Evaluation

- Automatic and quantitative evaluation metrics
  - · A list of high-frequency words in the whole data, except the common stop words in Chinese.
  - · A list of words left in real-time compressed sentences together with their labels and the corresponding frequencies.
- The Cohen's Kappa coefficient ⟶ **The inter-annotator agreement**
  - · The Cohen's unweighted k = 0.623 ⟶ A substantial level
- The Hopkins statistic ⟶ The **cluster tendency** of our data
  - · The value is around 0.719 – 0.726 ⟶ A high tendency to be clustered

Data Evaluation and Description

- ✓ Data Evaluation
- ✓ Data Description

<table>
<tr><td colspan="2">Total Number</td><td colspan="3">3300 (original query, compressed sentence) pairs</td></tr>
<tr><td colspan="2">Compression Ratio (CR)</td><td colspan="3">0.709</td></tr>
<tr><td rowspan="2">Total Words</td><td>Origin: 2,552</td><td rowspan="2">Sentence Length</td><td rowspan="2">Origin</td><td>2 - 48 (characters)</td></tr>
<tr><td rowspan="2">Compression: 2,291</td><td>1 - 28 (words)</td></tr>
<tr><td rowspan="2">Compression</td><td>2 - 37 (characters)</td></tr>
<tr><td>1 - 18 (words)</td></tr>
</table>

Note: $CR = \frac{The\ number\ of\ left\ words\ in\ the\ compressed\ sentences}{The\ total\ number\ of\ word\ in\ the\ original\ sentences}$

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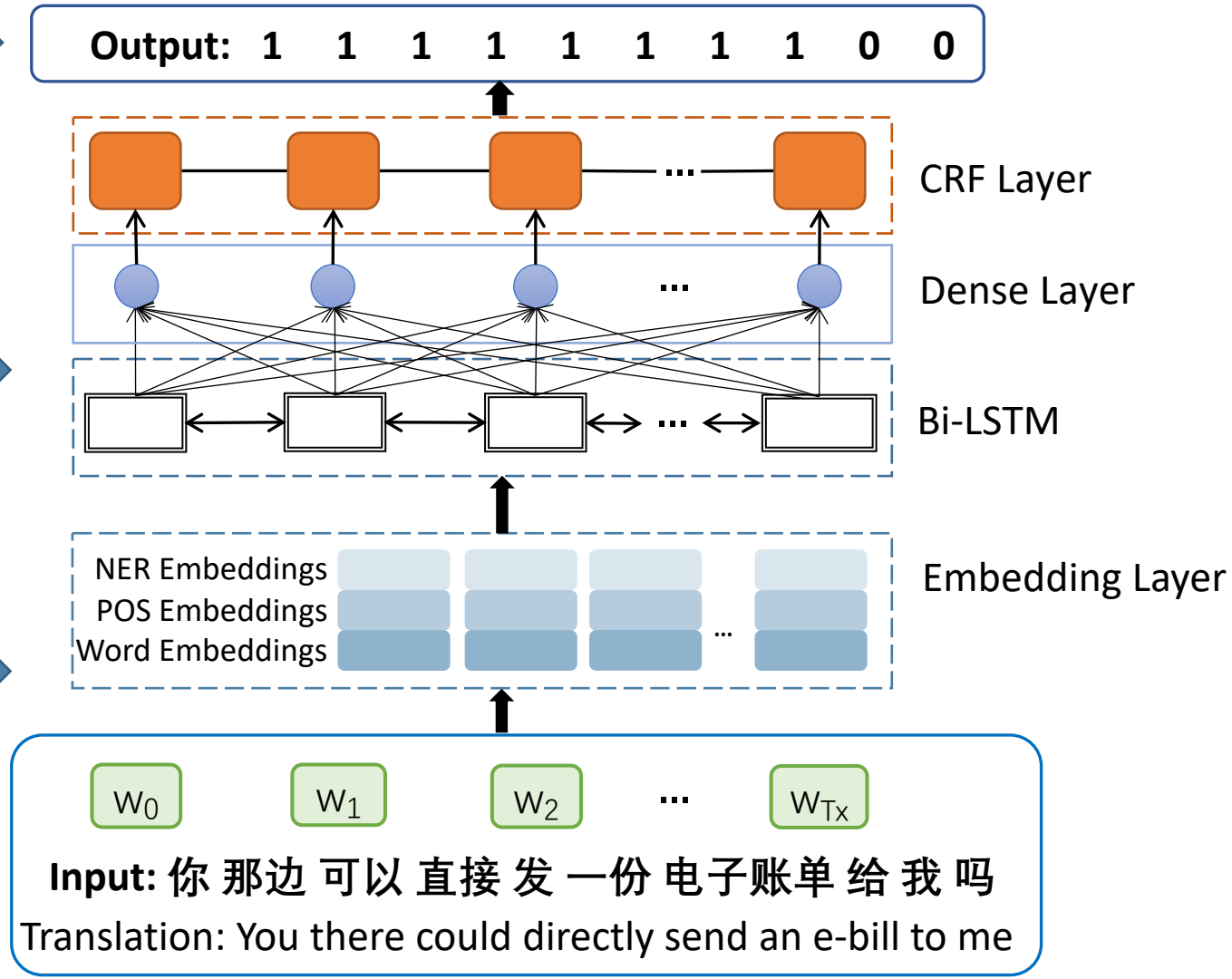
Baseline Model

Objective

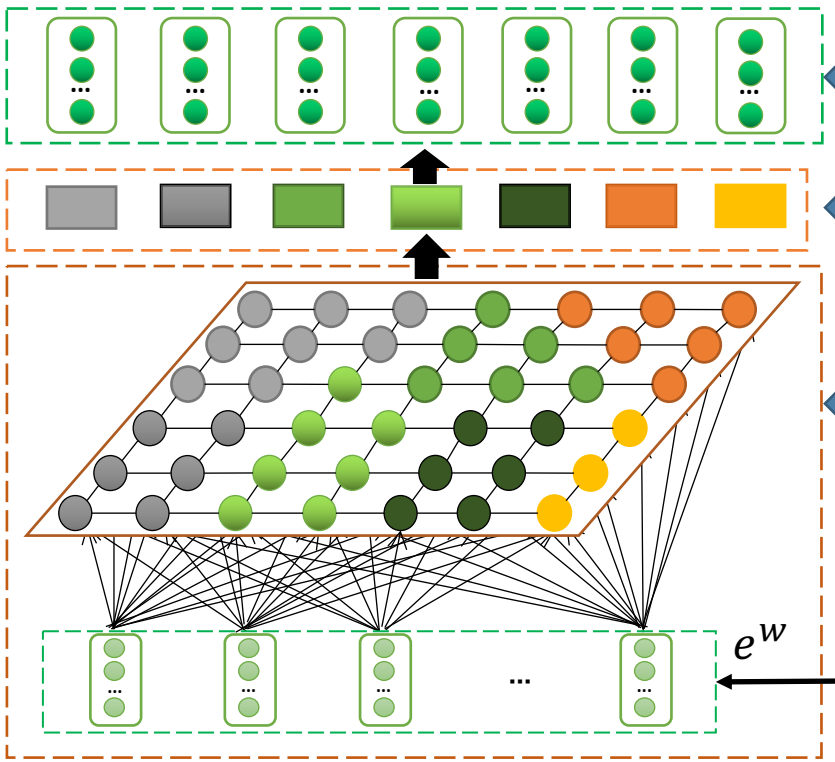
A commonly-used neural sequence labeling model: Bi-LSTM+CRF

Features: named entities (NE) features, part-of-speech (POS) features.



Pre-trained SOM

- For **better exploring the implication of our data and relieving the degree of data sparsity**, we apply a neural cluster model (the Self-Organizing Map, SOM) to obtain the cluster information of our data.



Cluster index embeddings

$z_s = som(e^w; \theta_s)$ → a mono-dimensional index

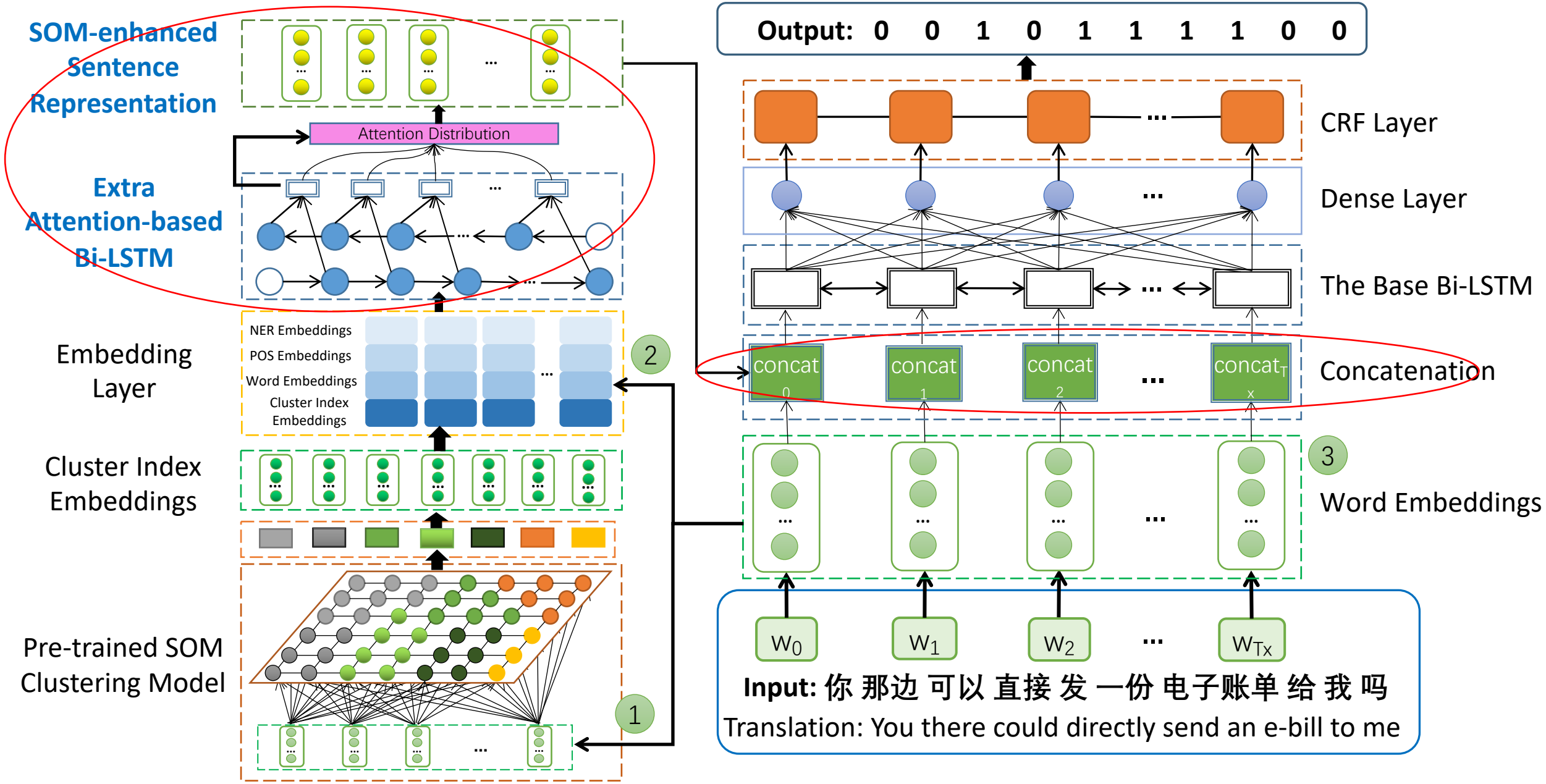
SOM: a feed-forward structure with a square output layer

w_0 w_1 w_2 ... w_{Tx}

Input: 你 那边 可以 直接 发 一份 电子账单 给 我 吗

Translation: You there could directly send an e-bill to me

SOM-NCSCM


SOM-enhanced Sentence Representation
Extra Attention-based Bi-LSTM
Attention Distribution
Embedding Layer
NER Embeddings
POS Embeddings
Word Embeddings
Cluster Index Embeddings
Cluster Index Embeddings
Pre-trained SOM Clustering Model
2
1
3
Output: 0 0 1 0 1 1 1 1 0 0
CRF Layer
Dense Layer
The Base Bi-LSTM
concat 0
concat 1
concat 2
concat T x
Concatenation
Word Embeddings
W0
W1
W2
WTx
Input: 你 那边 可以 直接 发 一份 电子账单 给 我 吗
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Main Results

Models	F1	BLEU1	BLEU2	BLEU3	BLEU4	CR
Chinese BERT-based model	85.785	73.442	64.253	58.295	53.911	0.833
Baseline	88.466	82.996	76.179	71.210	67.449	0.690
w/ SOM direct	88.228	81.162	76.214	70.804	66.645	0.649
w/o NE&POS	87.872	81.250	75.155	68.773	64.124	0.712
w/o NE&POS w/ SOM direct	87.991	82.313	75.948	69.861	64.431	0.702
K-Means + NCSCM	89.061	**84.238**	77.995	72.299	67.333	0.672
GMM + NCSCM	88.704	82.893	**79.201**	73.763	68.489	0.673
SOM-NCSCM	**89.655**	84.000	78.221	**74.766**	**70.116**	0.683

Training set: 3,000
Development set: 150
Test set: 150

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1. The scores of the fine-tuned Chinese BERT-based model don't reach fascinating points.
   · CR = 0.833 ⟶ Tends to **retain more words**.
   · It's easy to be **over-fitting**, due to the complex structure.

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2. All the models employed with lexical features (NE and POS features) perform better than those without them.
   · **The effectiveness of the lexical features**.

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3. Adding the cluster index features generally helps.

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3. Adding the cluster index features causes the performance to drop a little, compared to the standard baseline model.
   · Noises and sparsity problem.
   · The amount of dataset is not so large to make **a trade-off between fixing clustering mistakes and learning from cluster index features.**

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4. The efficient and feasible structure of our neural Chinese SC model.

→ The advantageous ability of the SOM, and the whole SOM-NCSCM can alleviate the effect of the shortage of parallel data while also make better use of similarity among data.

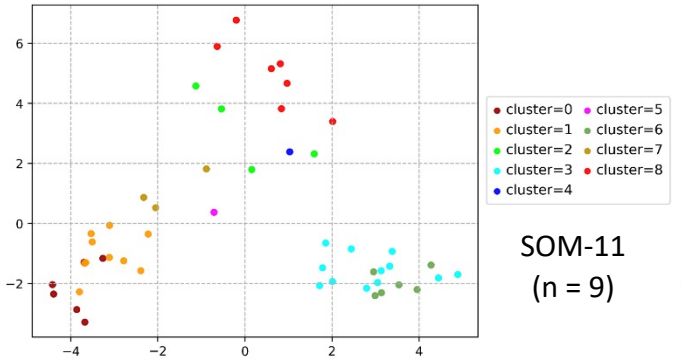
Analyses of Cluster Results

✓ Experiments on SOM parameters

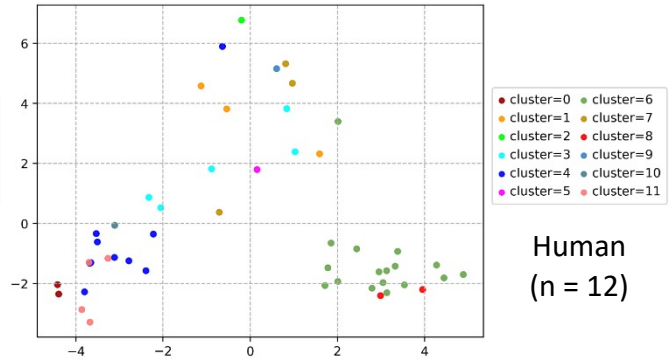
Our SOM-NCSCM					
SOM size	9 × 9	10 × 10	11 × 11	12 × 12	13 × 13
F1	89.299	88.704	**89.655**	88.466	88.823
BLEU1	83.908	81.227	**84.000**	83.206	81.132
BLEU2	**79.156**	76.425	78.221	77.663	75.552
BLEU3	74.263	70.606	**74.766**	73.876	71.400
BLEU4	**70.547**	66.207	70.116	70.016	66.470
CR	0.688	0.649	0.683	0.680	0.710
Number of Clusters	81	100	121	144	169

➢ **The Silhouette Coefficient scores and Calinski-Harabasz scores of all experimental models and human judgement on 50 randomly selected query sentences.**

✓ Cluster results of 50 Randomly-selected query sentences



SOM-11
(n = 9)



Human
(n = 12)

Model	Silhouette Coefficient Score	Calinski-Harabasz Score
K-Means	0.032	2.451
GMM	0.007	2.205
SOM-9	0.026	2.597
SOM-10	0.045	2.788
SOM-11	**0.071**	**4.066**
SOM-12	0.053	**3.002**
SOM-13	0.035	2.838
Human	**0.065**	2,945

➢ Manual judgement criteria: the user demands, the sentence length, the structure of original query sentences.

Case Studies

Original Query Sntence	你/那边/可以/直接/发/一份/电子账单/给/我/吗	你/要/给/记录/[编号]/号/客服代表/挂/我电话/的/问题
Translation in English	You there could directly send an e-bill to me	You should record for (me) the matter that the No. [number] customer service representative hangs up on me
Gold Compressed Sentence	发/一份/电子账单/给/我 Send an e-bill to me	[编号]/号/客服代表/挂/我电话 The No. [number] customer service representative hangs up on me
Chinese BERT-based model	{边}/可以/直接/发/{份}/电子/账单/给/我 {There} could directly send {an} e-bill to me	记录/[编号]/号/客服/代表/挂/我/电话/问题 Record the matter that the No. [number] customer service representative hangs up on me
Baseline	你/那边/可以/直接/发/一份/电子账单/给 You there could directly send an e-bill to	[编号]/号/挂/我电话/问题 The matter that the No. [number] hangs up on me
K-Means + NCSCM	发/一份/电子账单/给 Send an e-bill to	挂/我电话/问题 The matter that hangs up on me
GMM + NCSCM	可以/发/一份/电子账单 Could send an e-bill	号/挂/我电话/问题 The matter that the No. hangs up on me
SOM-NCSCM	可以/发/一份/电子账单/给 Could send an e-bill to	[编号]/号/挂/我电话/问题 The matter that the No. [number] hangs up on me

- There's some degree of gap between **getting exact matched results** with strict gold compressed sentences and producing acceptable outputs.

Case Studies

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- The fine-tuned Chinese BERT-based model keeps **the most characters** in its outputs.
  There are even some **incorrectly labeled words**.
  - Such as “那边” (there) and “一份” (an).

Case Studies

Original Query Sntence	你/那边/可以/直接/发/一份/电子账单/给/我/吗	你/要/给/记录/[编号]/号/客服代表/挂/我电话/的/问题
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- Mistaken deletion of the keyword “客服代表 (customer service representative)” in most of models.
  - · A **domain-specific** proper noun
  - · An unknown word in the pre-trained word embeddings
  - · It’s unrecognizable as a whole word phrase for the tools to label NE and POS tags.
- The Chinese BERT-based model can hold the correct word tokens but in a **different segmentation granularity**.

Conclusion

1. We construct **a Chinese SC dataset**, composed of Chinese colloquial sentences, from a real-life QA system in the telecommunication domain.
2. We build **several neural baseline models** and propose our **SOM-NCSCM** for Chinese SC task.

- We'll work on constructing a **larger Chinese SC dataset** and take more measures to ensure the quality of the dataset.
- We also plan to explore **domain-specific knowledge** and **other neural-network techniques** to deal with the Chinese SC task in the future.

Dataset is available at *https://github.com/Zikangli/SOM-NCSCM*.

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Thanks for your listening!

Kangli Zi, Shi Wang, Yanan Cao, Yu Liu, Jicun Li, Cungen Cao

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