A Corpus and Method for Chinese Named Entity Recognition in Manufacturing

Ruiting Li[1,2], Peiyan Wang[1,2]◈ ,
Libang Wang[1,2], Danqingxin Yang[1,2], Dongfeng Cai[1,2]
1. School of Computer Science, Shenyang Aerospace University, Shenyang, China
2. Liaoning Professional Technology Innovation Center on Knowledge Engineering and Human-Computer Interaction, Shenyang, China
liruiting@stu.sau.edu.cn, wangpy@sau.edu.cn
{wanglibang, yangdanqingxin}@stu.sau.edu.cn, caidf@vip.163.com

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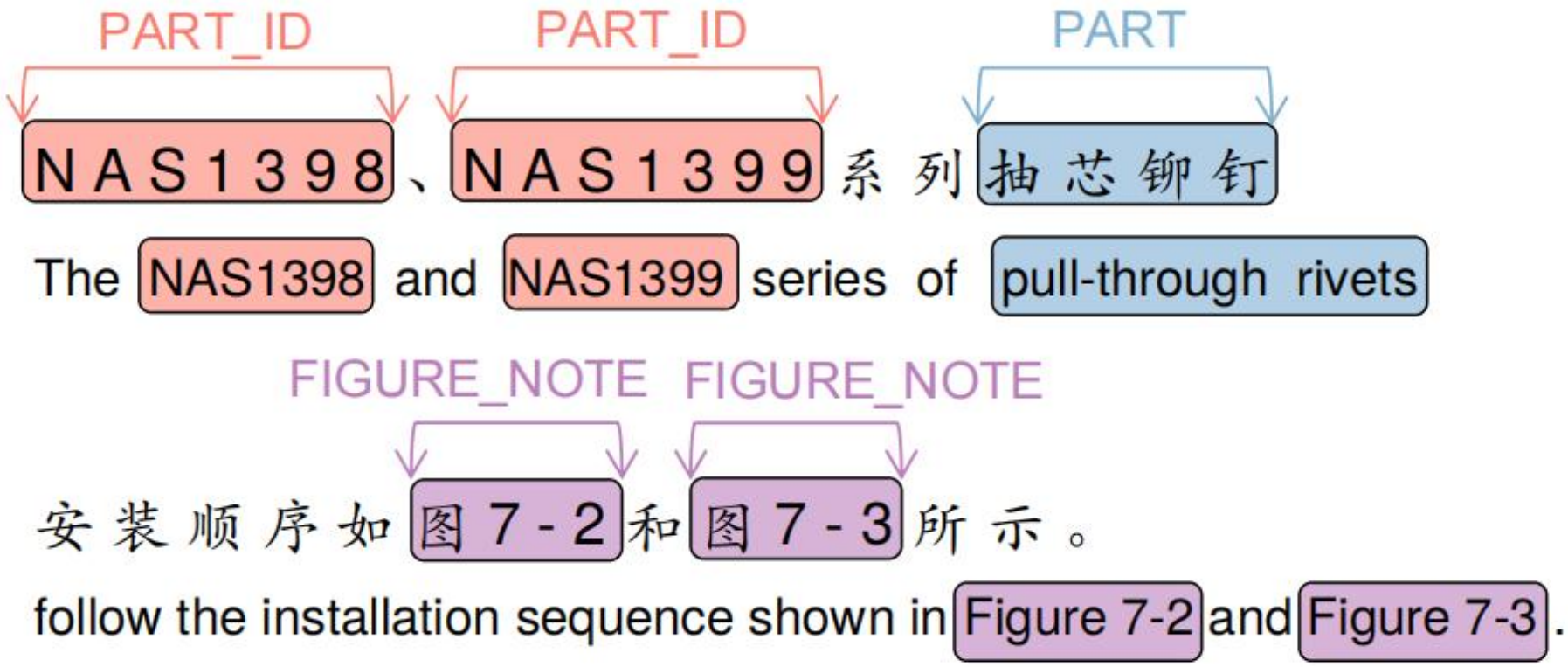
Introduction

NER in the manufacturing specifications aims to locate and classify manufacturing specific named entities such as PART_ID, PART and FIGURE_NOTE.



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  - High cost of manual annotation.

- Conventional neural methods perform poorly in manufacturing.
  - Conventional neural methods rely on a large amount of training data.
  - Sufficient labeled data is unavailable in manufacturing.

What We Have Done

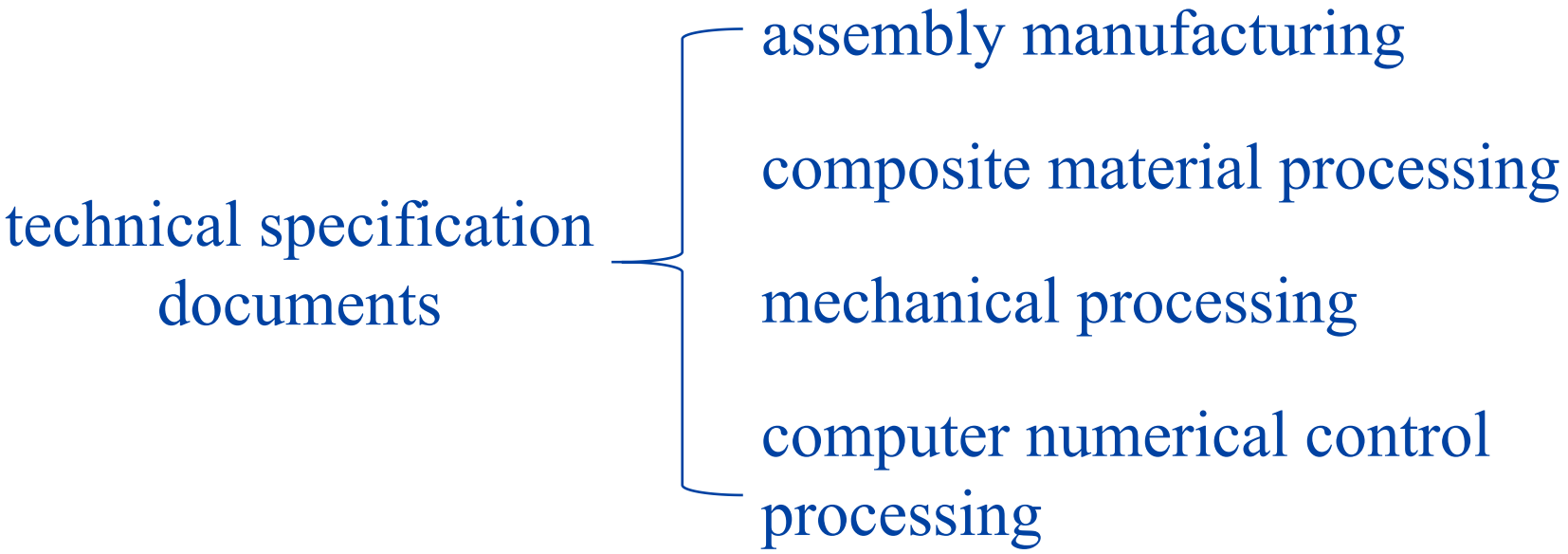
Our key contributions are the following:

- Annotation guidelines for NER corpus in manufacturing, including annotation instructions and definitions for 16 categories such as PART, PART_ID, FILE, and FIGURE_NOTE.

- A Chinese NER corpus named MS-NERC with 4,424 sentences and 16,383 entities.

- An entity recognizer named Trainable States Transducer for modeling morphological patterns of named entities.

Text Collection



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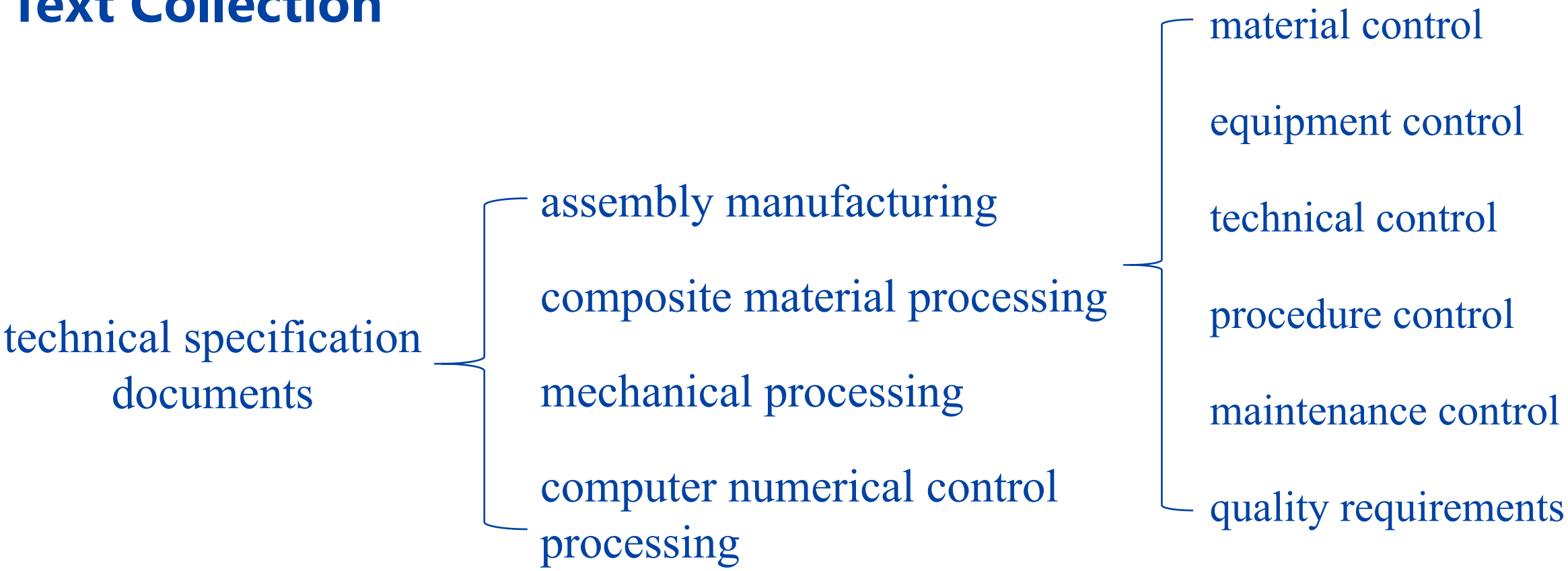

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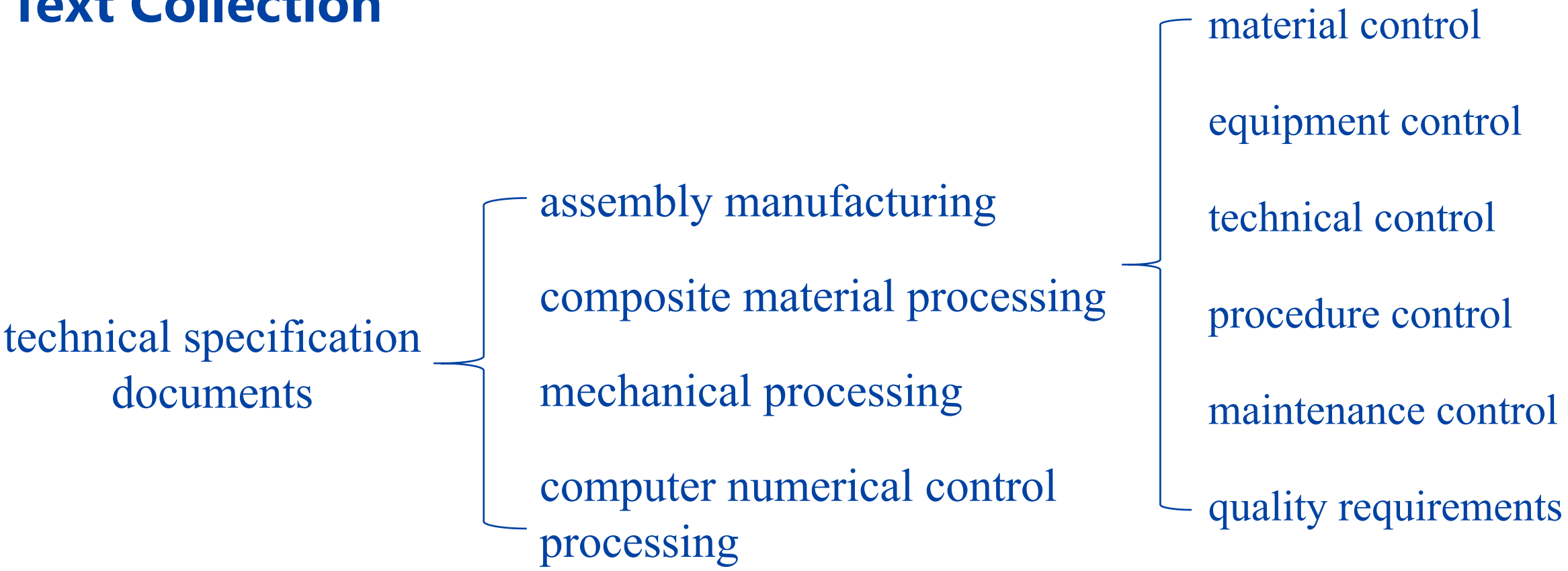

- Manufacturing parameters and manufacturing conditions. ✔
- Information related to specific products and enterprises. ✘
- A raw dataset of 4,424 sentences.

Annotation Guidelines

16 categories refer to the Fundamental Terminology of Mechanical Manufacturing (Hongyu et al.,2008).

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- PART_ID marks an identification number assigned to the part.
  (e.g., NAS1398).

- PART marks a basic component unit in manufacturing, including the combination of parts.
  (e.g., 抽芯铆钉 / pull-through rivet)

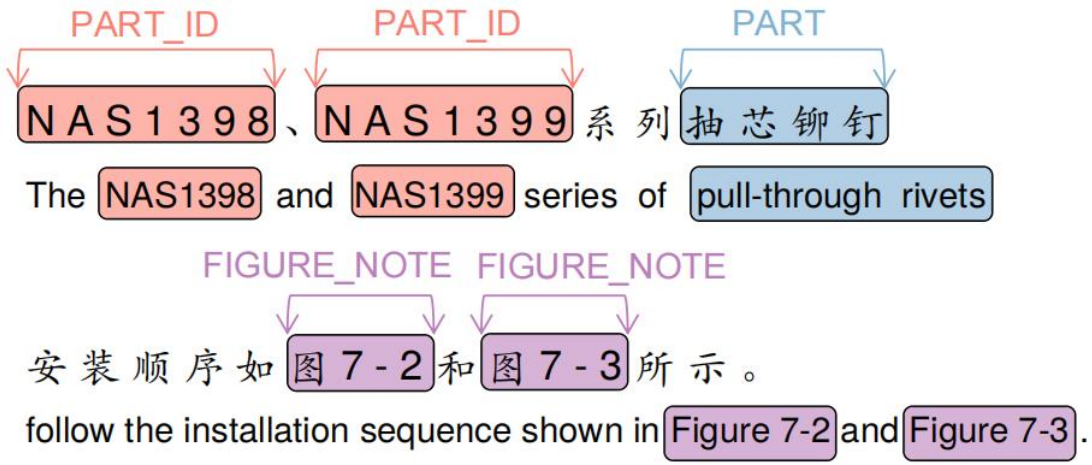

Figure 1: Examples of the sentence with named entities and translations in the manufacturing specifications.

Annotation Guidelines

Three specific instructions:

- The entities must be specific rather than generalized .
  (e.g., ’铆钉’ /rivet instead of ’零件’/part)

- The entities should not be accompanied by conjunctions and punctuation marks indicating juxtaposition, except in the case of notes in parentheses.
  (e.g., ’1.02mm(0.040in.)’)

- The entities are annotated based on their maximum span without nesting.

Annotation Process

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- Formal annotation commences once a Cohen's Kappa (Cohen, 1960) score exceeding 0.6 is achieved. Our inter-annotator agreement is 0.68.

MS-NERC Statistics

The corpus comprises a total of 4,424 sentences and 16,383 entities.

Category	Number	Max	Min	Mean
ACCESSORY	1,861	12	1	3.31
ACCESSORY_ID	876	17	3	7.87
ATTRIBUTE	2,479	19	1	3.54
ATTRIBUTE_VA	1,357	50	1	10.85
FIGURE_NOTE	396	6	3	4.21
FILE	556	12	3	6.82
HOLE	418	12	1	2.14
MATERIAL	481	13	1	3.27
OPERATION	1,933	9	1	2.63
PART	2,407	13	1	3.27
PART_AR	1,396	14	1	3.85
PART_ID	202	15	2	8.75
PART_NU	131	4	1	1.89
REDUNDANT	164	6	1	2.27
TABLE_NOTE	296	6	3	4.05
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Table 1: Entity statistics in *MS-NERC*.

Category	Example	REs
ACCESSORY_ID	RQI5275	RQI(\d){4}
ATTRIBUTE_VA	-28.6m	-(\d+).(\d+)m
FIGURE_NOTE	图6-20	图(\d+)-(\d+)
FILE	RQX3001	RQX(\d){4}
PART_ID	NAS1252	NAS(\d+)
TABLE_NOTE	表7-1	表(\d+)-(\d+)

Table 2: Examples of entities and regular expressions.

Regular Expressions and Finite State Transducer

PART_ID PART_ID FIGURE_NOTE FIGURE_NOTE

NAS1398、NAS1399系列抽芯铆钉安装顺序如图7-2和图7-3所示。

The NAS1398 and NAS1399 series of pull-through rivets follow the installation sequence shown in Figure 7-2 and Figure 7-3.

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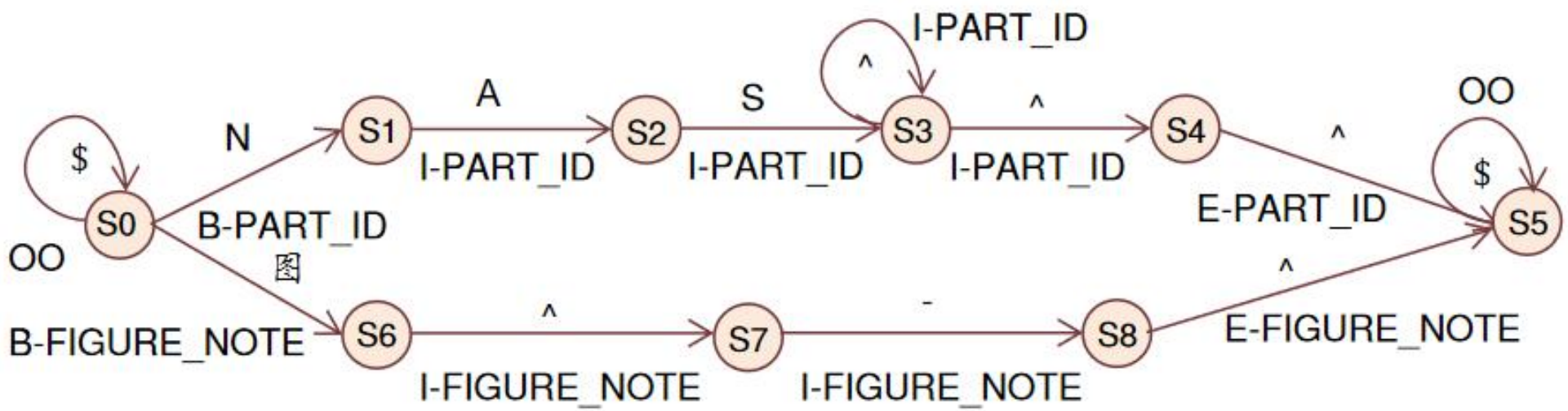
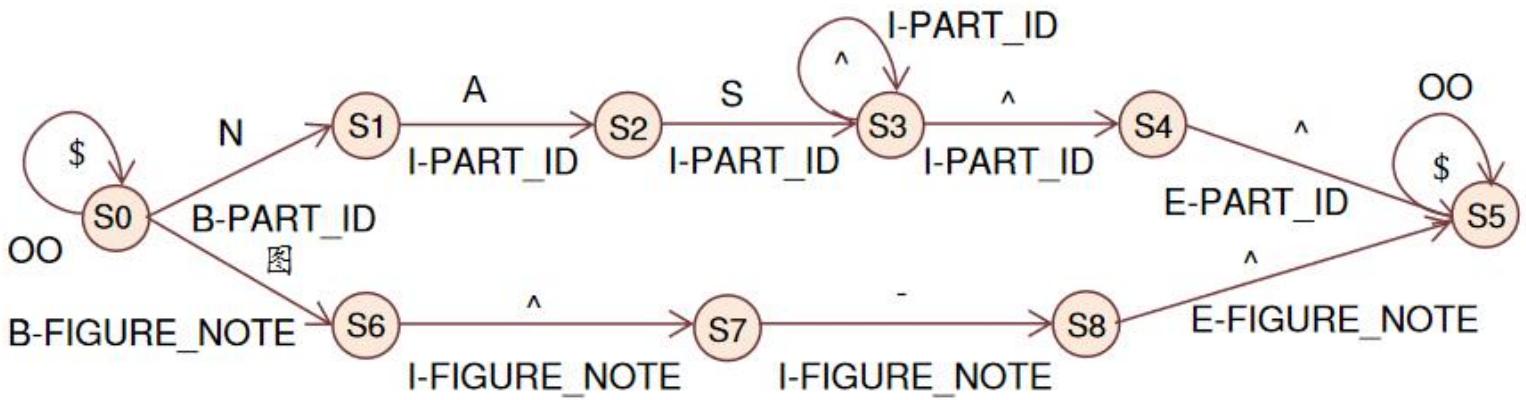


Parameter Tensors for TST



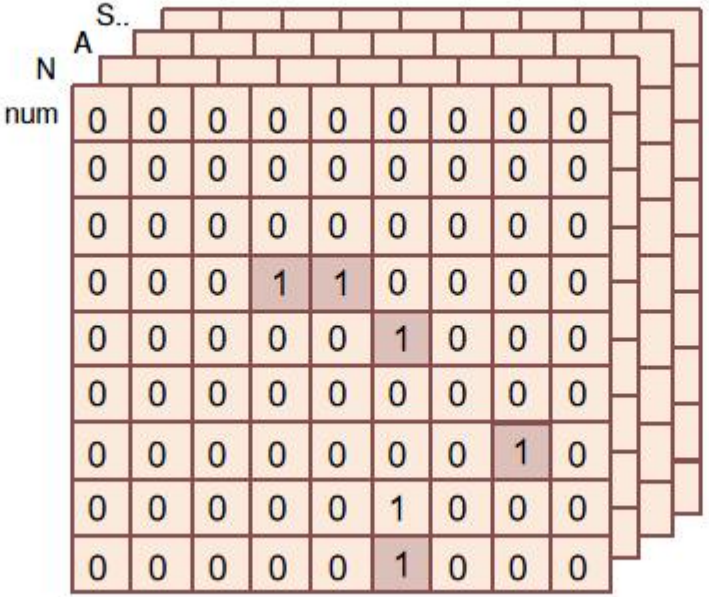
Parameter of TST

1	0	0	0	0	0	0	0	0

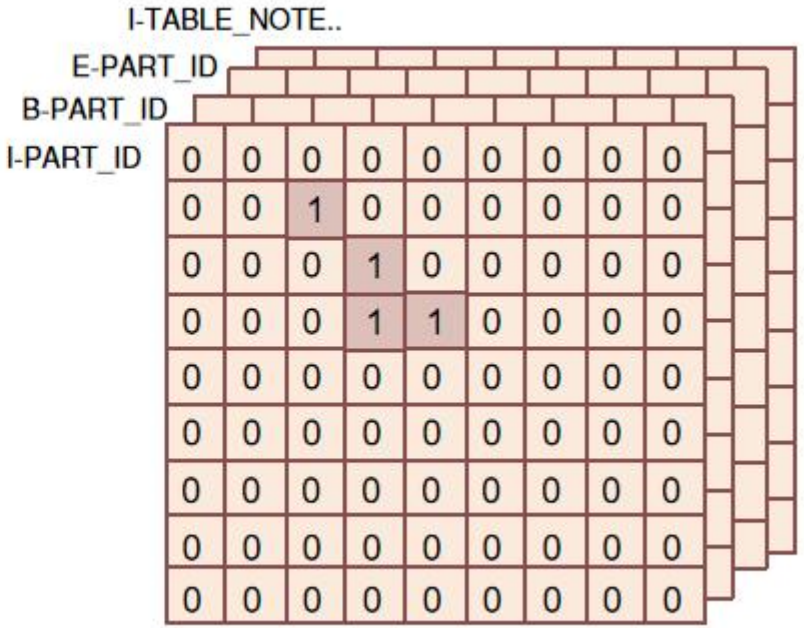
s

0	0	0	0	0	1	0	0	0

m



w_i



w_o

TST Inference

Given a sentence $x = (x_1, x_2, ..., x_n)$, and TST.

Algorithm 1 Inference in *TST*

Input: $x = (x_1, x_2, ..., x_n)$,
$\mathcal{N} = \langle \mathcal{S}, \mathcal{I}, \mathcal{O}, W_i, W_o, s, m \rangle$.
Output: the label scores f_t of x_t.
Step 1: Let $\odot$ denote hadamard product, $\otimes$ denote outer product.
Let $\alpha_0 = s^{\mathsf{T}}, \beta_n = m^{\mathsf{T}}$.
Step 2: calculate forward score α_t
for $t = 1 \rightarrow n$ **do**
  $\alpha_t = W_i[x_t] \cdot \alpha_{t-1}$
end
Step 3: calculate backward score β_t
for $t = n \rightarrow 1$ **do**
  $\beta_t = W_i^{\mathsf{T}}[x_t] \cdot \beta_{t+1}$
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Step 4: calculate bidirectional score bi_scores
for $t = 1 \rightarrow n$ **do**
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$$P_t = priority\left(W_p\left(f_t + f_t'\right) + b_p\right)$$

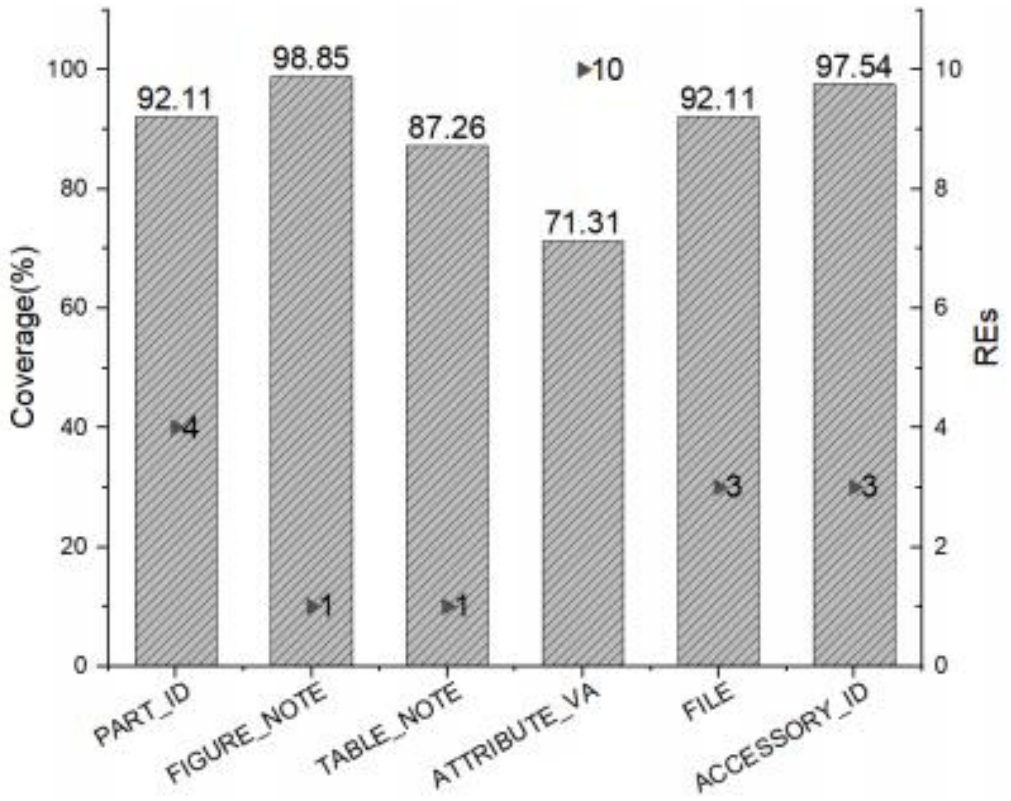
$$P_t' = \left(\max\left(p_1', p_k'\right), p_2', p_3', \ldots, p_{k-1}'\right)$$

$$l_t = \underset{1 \le j \le k-1}{argmax}\, P_t'(j)$$

Dataset and Regular Expressions

- MS-NERC: 70% sentences as the training set, 10% as the development set, and 20% as the testing set.

- Regular Expressions:



Zero-shot Experiment

Type	*TST*	REs
ACCESSORY_ID	96.81	97.08
ATTRIBUTE_VA	63.41	56.63
FIGURE_NOTE	96.97	98.20
FILE	92.98	88.98
PART_ID	58.06	75.51
TABLE_NOTE	97.67	97.67
micro-average	82.05	78.76

Table 6: F1 scores (%) for the initial *TST* and REs in zero-shot.

Rich-resource Experiment

Three baselines:

- PER (Jia et al., 2022): a specialized NER method in manufacturing.
- BILSTM (Siami-Namini et al., 2019) is one of the prominent deep learning models employed for addressing sequence-related tasks.
- TENER (Yan et al., 2019) utilizes the Transformer architecture to model information for NER tasks.

Rich-resource Experiment

	P	R	F1
TST	**65.96**	61.27	**63.53**
PER	58.07	**67.2**	62.3
BILSTM	55.28	64.67	59.61
TENER	53.37	63.98	58.19

Table 7: Micro-average F1 scores (%) for *TST* and baselines in rich-resource.

Rich-resource Experiment

	P	R	F1
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BILSTM	55.28	64.67	59.61
TENER	53.37	63.98	58.19

Table 7: Micro-average F1 scores (%) for *TST* and baselines in rich-resource.

Few-shot Experiment

Four baselines:

- PER (Jia et al., 2022): a specialized NER method in manufacturing.
- Template-based BART (Cui et al., 2021): a template-based method for exploiting the few-shot learning potential of generative pretrained language models to sequence labeling.
- Prompt-Slot-Tagging (Hou et al., 2022) reversely predict slot values based on provided slot types. This approach incorporates training by considering the relationships between different slot types.
- NNShot (Yang and Katiyar, 2020) is a method based on nearest neighbor learning and structured inference. This approach uses a supervised NER model trained on the source domain, as a feature extractor.

Few-shot Experiment

- N-shot: N entities of each entity category.
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	20-shot	50-shot	3%-sen	6%-sen
init-*TST*		29.51		
TST	26.7	**31.24**	**25.77**	**36.7**
PER	0.61	4.8	0.87	6.81
Template-based BART	12.52	15.68	13.87	17.54
Prompt Slot Tagging	16.38	17.08	17.44	23.2
NNShot	**27.2**	30.5	25.25	29.37

Table 8: Micro-average F1 scores (%) for *TST* and baselines in few-shot.

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Thanks for your time!