MLRIP: Pre-training a military language representation model with informative factual knowledge and professional knowledge base

Hui Li\textsuperscript{1}, Xuekang Yang\textsuperscript{1}, Xin Zhao\textsuperscript{2}, Lin Yu\textsuperscript{1}, Jiping Zheng\textsuperscript{3} and Wei Sun\textsuperscript{4}

\textsuperscript{1}School of Automation, Nanjing University of Science and Technology, Nanjing, China
\textsuperscript{2}The 28th Research Institute of China Electronics Technology Group Corporation, Nanjing, China
\textsuperscript{3}North Information Control Research Academy Group Co., Ltd., Nanjing, China
\textsuperscript{4}Changan Wangjiang Group Co., Ltd., Chongqing, China

Abstract

Incorporating prior knowledge into pre-trained language models has proven to be effective for knowledge-driven NLP tasks, such as entity typing and relation extraction. Current pre-training procedures usually inject external knowledge into models by using knowledge masking, knowledge fusion and knowledge replacement. However, factual information contained in the input sentences have not been fully mined, and the external knowledge for injecting have not been strictly checked. As a result, the context information cannot be fully exploited and extra noise will be introduced or the amount of knowledge injected is limited. To address these issues, we propose MLRIP, which modifies the knowledge masking strategies proposed by ERNIE-Baidu, and introduce a two-stage entity replacement strategy. Extensive experiments with comprehensive analyses illustrate the superiority of MLRIP over BERT-based models in military knowledge-driven NLP tasks.

1 Introduction

Pre-training language representation models on large-scale heterogeneous text of corpora with unsupervised or weakly-supervised objectives like masked language model (MLM) can benefit downstream natural language processing (NLP) tasks such as entity typing, relation extraction (RE), and entity typing. ELMo (Peters et al., 2018), OpenAI GPT (Radford et al., 2018), and BERT (Devlin et al., 2018) are trained on large-scale corpus and have been widely used in open-domain NLP tasks, which have significantly promoted the downstream performance even gain the state-of-the-art (SOTA). For domain-specific, many domain-specific language representation models have been proposed such as BioBERT (Symeonidou et al., 2019), FinBERT (Araci, 2019), SciBERT (Beltagy et al., 2019), and PatentBERT (Lee and Hsiang, 2020), which have achieved the SOTA performance on various domain-specific NLP tasks. Despite these pre-trained models have gained huge success in empirical studies, latest studies show that efforts with weakly-supervised manners (Xiong et al., 2019, He et al., 2019, Bosselut et al., 2019) outperform that with unsupervised manners.

Recently, many researchers have devoted to using various strategies to incorporating external knowledge, be it KGs, annotations, or unstructured texts, into language representation models such as ERNIE-Baidu (Sun et al., 2019), ERNIE-Tsinghua (Zhang et al., 2019), K-ADAPTER (Wang et al., 2020), etc., and have established new SOTA on downstream NLP tasks. As a result, injecting knowledge into language representation models have become a mainstream for NLP.

However, these promising models cannot be directly used in military domain for the following reasons: (1) contextualized word representations such as ELMo, OpenAI GPT, BERT, XLNet (Yang et al., 2019), and ERNIE-Baidu are trained and tested mainly on general corpus (Wikipedia and BookCorpus), it is difficult to estimate their performance on military text mining. (2) The language and vocabulary used in military texts is dramatically different than a general one, thus word distributions of general and military corpora are quite different, which can often be a problem for military text mining. (3) Pre-training tasks are designed with respect to the corpora and entity features in general texts, which are not suitable for military text mining, domain-specific pre-training tasks should be developed accordingly. (4) Domain-specific characteristics such as multiple representation styles, semantic vague, wide variation in literal meaning from text to text, etc., are not contained in general texts.

In addition, the vast majority of existing pre-training models learn word representation by using masked language model (Devlin et al., 2018, Liu et al., 2019) or knowledge masking (Sun et al., 2019, Joshi et al., 2020, Cui et al., 2021) strategy with attention mechanism, or by injecting external knowledge into models (Xiong et al., 2019, He et al., 2019, Liu et al., 2021). However, there are limitations for using these methods: (1) masked language model can only model low level semantic knowledge (Sun et al., 2019), (2) knowledge masking strategies have mod-
eled more lexical, syntactic, and semantic information into pre-training model, but they have not taken full advantage of the factual information contained in the input sentences, which have been illustrated in Figure 2. (3) knowledge enhanced methods have neglected the problem existed in the knowledge source, for example, the knowledge may be wrong, some knowledge is not contained and other situations. In this thesis, we propose a model named MLRIP. We follow the knowledge masking strategies proposed by Sun et al. (2019), but we modify these strategies by explicitly adding prior factual knowledge contained in the input sentences to help predicting masking units, also we add a relation-level masking method to augment the representation for prior knowledge. Furthermore, we propose a two stage entity replacement strategy to incorporate more domain-specific knowledge into the representation model. First, we apply same-entity mention to replace the origin mention which enable MLRIP to learn entity mention knowledge, meanwhile, we introduce a negative sample strategy for entity mentions replacement. Based on this, we use the fact-based replacement strategy to inject domain-specific prior knowledge into the model.

To evaluate the performance of our proposed model MLRIP, we first construct a set of benchmark datasets for comparison, and then we conduct experiments on two knowledge-driven NLP tasks, i.e., entity typing and relation classification. The experimental results show that MLRIP significantly outperforms BERT and ERNIE-Baidu, by taking full advantage of lexical, syntactic, and factual knowledge information within sentences, and knowledge from domain-specific knowledge base. We also evaluate MLRIP on military NER, and MLRIP still achieves comparable results. In addition, we perform ablation studies on all the strategies and the corresponding experimental present that our strategy achieve improvement individually and benefit downstream tasks accordingly.

In summary, our contributions are as follows:

- We propose a model named MLRIP for military text mining, and we introduce a new knowledge masking strategy for training language representation model, and also, we introduce a new knowledge incorporation method for injecting military domain-specific knowledge into language representation model.
- Our model has significantly promoted the performance for knowledge-driven military NLP downstream tasks, such as entity typing and relation extraction.
- We construct various benchmark datasets for military text mining.

2 Related Work

External knowledge, be it knowledge graphs (KGs), domain-specific data, extra annotations or professional knowledge base, is the outcome of human wisdom, which can be good prior knowledge for enhancing the language representation model. ERNIE-Baidu (Sun et al., 2019) proposes to use knowledge masking strategies to enhance the language representation. It introduces phrase-level masking and entity-level masking and predicts the whole masked phrases and entities in the sentences to help the model learn syntactic, sentiment and dependency information both in local contexts and global texts. ERNIE-Tsinghua (Zhang et al., 2019) enhances the language representation in another way, which incorporates knowledge graph into BERT to learn lexical, syntactic and knowledge information simultaneously by aligning entities from Wikipedia sentences to fact triples in WikiData. BERT-MK (He et al., 2020) regards the sub-graphs in KGs as a whole, and directly model them and the aligned text to retain more structural information, then integrated with a pre-trained language model to perform the knowledge generalization. K-ADAPTER (Wang et al., 2020) proposes a plug-in way to inject knowledge into large pre-trained language models, which keeps different kinds of knowledge in different adapters. WKLM (Xiong et al., 2019) propose an effective weakly supervised pretraining objective to force the model to incorporate knowledge about real-world entities, which replaces entity mentions in the original document with the names of other entities that have the same type as the mentioned one and predict whether the entity has been replaced. OAG-BERT (Liu et al., 2021) integrates heterogeneous structural knowledge in the open academic graph, which can directly convert structural knowledge into the serialized text and let the model learn knowledge-text alignments by itself. ERICA (Qin et al., 2020) proposes to explicitly model relational facts in text via entity discrimination task and relation discrimination task to better understand entities and relations, and the tasks are performed by leveraging contrastive learning strategy.

3 Methods

In this section, we introduce MLRIP and its detailed implementation. We first describe the model architecture in section 3.2, the embedding layer in section 3.3, the novel pre-training tasks knowledge integration strategy and fact-based entity replacement in section 3.4 and section 3.5 respectively, and the details for pre-training in section 3.6.
3.1 Notation
We denote an input sentence $s = \{w_1, w_2, \ldots, w_n\}$ as a token sequence, where $n$ is the length of the given sentence, $w_i, i \in [0, n]$ denotes a word token in the sequence. Meanwhile, we denote the encoded input sequence as $enc(s) = \{x_1, x_2, \ldots, x_n\}$. Note that, in this thesis, we treat English tokens at word-level, while Chinese tokens at character-level. Furthermore, we denote the whole token vocabulary as $V$, and the military entity list containing all entities in military entity dictionary as $E$.

3.2 Model Architecture
We follow most knowledge-enhanced language representation model (Sun et al., 2019; Zhang et al., 2019; Qin et al., 2020), use multi-layer Transformer as basic encoder. The transformer adopts self-attention mechanism to capture lexical, syntactic, sentiment, and semantic information from the input sentences, and generates a corresponding sequence of contextual embeddings for downstream natural language understanding tasks, such as NER, entity typing, RE, etc. In detail, we denote the stacked transformer encoder layers as $L$, masked self-attention heads as $A$, and the hidden dimension as $H$. Then we have the following model size configuration: $L = 12$, $A = 12$ and $H = 768$. The total amounts of trainable parameters are the same as BERT\textsubscript{base} (110M), indicating that our model is compatible with BERT in model parameters.

3.3 Embedding Layer
We use the text type embedding to indicate the pre-training corpus types and the text features contained in them, as the word distributions and entity mention forms are quite different for corpus from various sources while these corpus features are important for some domain-specific, cross-domain and knowledge-driven tasks such as military NER and entity typing. We assign an $id$ to different training corpus, ranging from 1 to $N$, and each $id$ denotes one kind of training corpus. The corresponding token, segment, position and text type embedding are taken together to consist the input for our model, i.e., the input embedding is the sum of token embedding, segment embedding, position embedding, and text type embedding, and this is illustrated in Figure 1.

3.4 Knowledge Integration Strategy
Injecting prior knowledge into pre-trained language representation models can effectively improve the performance of the downstream tasks, which have been proven by many research works of knowledge-enhanced pre-training. We apply a multi-stage knowledge masking strategy as ERNIE-Baidu (Sun et al., 2019), but we make some changes to adapt to the military domain. Firstly, we adjust some masking mechanism, and then add a relation-level masking stage. The comparisons of MLRIP and ERNIE-Baidu are shown in Figure 2. In this section, we will introduce these strategies and their detailed implementation.

![Figure 1: The structure of the MLRIP model.](image)

*Figure 1: The structure of the MLRIP model. The input embedding contains the token embedding, the segment embedding, the position embedding and the text type embedding. Various pre-training tasks can be conducted based on this structure.*

![Figure 2: The different masking strategy between MLRIP and ERNIE-Baidu (Sun et al., 2019).](image)

*Figure 2: The different masking strategy between MLRIP and ERNIE-Baidu (Sun et al., 2019). In basic-level masking and phrase-level masking stage, the prediction process is consistent. In entity-level maskiing stage, we both apply MLM and $FKP_{E+R}$ to predict all slots in masked entities, instead of using MLM only. Furthermore, we add a relation-level masking strategy compared with ERNIE-Baidu, which also both use MLM and $FKP_{E+R}$ to predict each slot of the masked relation. Moreover, we inject external knowledge into MLRIP by introducing two novel replacement strategies: same entity mention replacement and fact-based knowledge replacement, respectively.*

3.4.1 Word-Level Masking
Word-level masking is the basic knowledge integration stage, aiming to learn the basic lexical, syntactic, semantic knowledge of the input sequence.
In this stage, the masking and prediction mechanism is consistent with BERT (Devlin et al., 2018). In the training procedure, 15% tokens are randomly masked and prediction task is performed, then the parameters of our model are updated, since that we can obtain a basic word representation model. Since the masked tokens are not always continuous in the word-level masking stage, the high-level semantic information contained in the input sentences, such as phrases, entities and relations, is hard to be fully explored.

3.4.2 Phrase-Level Masking

In this thesis, phrase mask is also applied to enhance the word representation. Similar to ERINE-Baidu, we treat the phrase contained in the input sequence as a whole unit like a word-level unit to perform mask and prediction. As phrase-level masking is identical to its implementation in ERINE-Baidu, we exclude a comprehensive description of this strategy and refer reader to Sun et al. (2019). At this stage, semantic information of the phrase is encoded into the model and we can obtain a word representation model with richer phrase information.

3.4.3 Entity-Level Masking

In this stage, we explore how to incorporate the entity information into the word representation model. In military domain, operational entities, such as weapons, military person, military locations, military organizations, etc., are the principal interest for military intelligence analysis and situational analysis. Usually, the entity pairs and the relation between them contained in a sentence are informative knowledge, including rich semantic information and always form some factual tuple, which are crucial clues for understanding the whole sentence even the whole text. However, the previous pre-trained representation models usually regard words as basic research unit or only consider the relation and entity as a dependent part, ignoring the relation between them.

For example, “A UH-60 was shot down by a FIM-92 this morning.”, intuitively, we can know that \( \langle UH - 60, \text{shot down}, FIM - 92 \rangle \), which is a factual knowledge in the military domain that can be used to predict the entity of “UH-60” and “FIM-92”. However, this kind of knowledge has not been exploited in the previous works, which only concern the entities themselves and ignore the factual information contained in the sentence. In this thesis, we propose a modified and novel strategy to predict all slots in the entities, which divides the prediction process into two parts: (1) factual knowledge prediction (FKP), (2) and MLM. FKP refers to using factual knowledge to predict the masked slots in the masked entity, which enable the model to learn the factual knowledge contained in the input sentence. MLM is the same as BERT and other contextualized word representation model. Then we sum the loss of FKP and MLM to predict each masked entity slots, which takes fully use the contextual information and factual knowledge, the whole procedure is depicted in Figure 3. For military corpus, we discard the sentences that no factual knowledge is contained, then we apply military dictionary, chunking tool, domain-specific knowledge and dependency parser tool to obtain the entities, relations, and factual tuples. In the training process, we only mask one of the entities in a factual knowledge to ensure the factual knowledge can be used to perform prediction.

With respect to FKP, to be specific, given a token sequence \( s = \{w_1, w_2, \ldots, w_n\} \) and its corresponding factual tuple \( \langle h, r, t \rangle \). Assuming that entity \( h \) is masked, we first encode the masked sequence with transformer encoder and obtain representations for each token in the sequence. We denote \( enc(s) = \{x_1, x_2, \ldots, x_n\} \) as the token representations, and then we apply \textit{mean pooling} operation over tokens that constitute entity \( t \) and relation \( r \) to obtain entity representation \( e_t \) and relation representation \( e_r \), then \( e_t \) and \( e_r \) can be represented as:

\[
e_t = \text{MeanPool}(x_{\text{start}(t)}, \ldots, x_{\text{end}(t)}) \quad (1)
\]

\[
e_r = \text{MeanPool}(x_{\text{start}(r)}, \ldots, x_{\text{end}(r)}) \quad (2)
\]

where \( \text{start}(\cdot) \) and \( \text{end}(\cdot) \) are used to calculate the start and end positions. We represent each token \( e_{h(i)} \) with \( e_r \) and \( e_t \), and its position embedding:

\[
e_{h(i)} = f(e_t, e_r, p_{i+\text{start}(h)}) \quad (3)
\]

where position embeddings \( p_1, p_2, \ldots \) indicate absolute positions of the masked tokens, \( p_{i+\text{start}(h)} \) denotes the position embedding for the \( i \)-th token of \( h \), \( i \) is relative to the start position. We follow SpanBERT (Joshi et al., 2020) and use a 2-layer feed-forward network with GeLU activations and layer normalization as the implementation for function \( f(\cdot) \), then the whole transfer procedure can be formulated as:

\[
h_0 = [e_t, e_r, p_{i+\text{start}(h)}] \quad (4)
\]

\[
h_1 = \text{LayerNorm}(\text{GeLU}(W_1h_0)) \quad (5)
\]

\[
e_{h(i)} = \text{LayerNorm}(\text{GeLU}(W_2h_1)) \quad (6)
\]

then we use the word representation \( e_{h(i)} \) to predict the \( i \)-th token of \( h \), and compute the cross-entropy loss.

MLRIP sums the loss both MLM and FKP:

\[
\mathcal{L}(h(i)) = \mathcal{L}_{\text{MLM}}(h(i)) + \mathcal{L}_{\text{FKP}_{E+R}}(h(i)) = -\log P(h(i)|x_{i+\text{start}(h)}) - \log P(h(i)|e_{h(i)}) \quad (7)
\]

where \( \text{FKP}_{E+R} \) indicates that we use one entity either head or tail for the given factual tuple and the relation to predict the other entity, i.e.,
In this section, we propose a two-stage knowledge injecting strategy to integrate entity multiple representation forms and external factual knowledge into the language representation model.

3.5 Entity Replacement Strategy

3.5.1 Same Entity Mention Replacement

It is interesting and common that one military entity can be represented as many forms, such as J-10, J10, F-10 or Vigorous Dragon, they are the mentions for a Chinese Third Generation Fighter, i.e., these mentions all refer to the same entity, and we named it coreference phenomenon. Many important downstream tasks, such as QA, entity typing, knowledge completion, semantic similarity analysis, etc., rely on coreference resolution. In order to effectively identify the mentions for entities, we pre-train the model with a same entity mention prediction task that enable the model to capture this knowledge.

The first replacement stage is to use different mentions to replace the entity mention selected in the training process, as depicted in Figure 5. As in the entity masking stage, we first analyze factual knowledge in a sentence, and find out whether tail entities contain multiple representation forms. Note that we mainly concern the tail entity in the factual knowledge. In the training process, we randomly select one of the tail entities to perform replacement and predict whether it refer to the same entity with the original mention. When replacing entity mentions, we first look up all the mentions for the entity from the mention dictionary (constructed in the data preparing process, and we maintain a military entity dictionary $E$, covering 148 types and 5,775 individuals, the dictionary contains fields: id, official name, type, other names, basic info, and so on, and stored in json form), and then we introduce a novel negative sample replacement strategy. We consider the corresponding mentions as positive $E^+$ samples listed in the military dictionary, and others as negative $E^-$ samples.

Specially, when doing replacement, 30% of the time...
the mention keep constant for preventing catastrophic forgetting of the original mention, and in the rest time, 50% of that mention is replaced from the candidate mentions set \( E_t = (e_t^1, e_t^2, \ldots, e_t^n) \), \( E_t \) denotes the candidate mention set, \( E^+ \) denotes a candidate mention vector for the entity \( t \), and \( E^- \) denote a random mention vector. Note that, we select a mention from the candidate mentions after replacing and encoding, we can obtain the distance between each candidate mention and the original mention, and then we obtain the selection probabilities by using Softmax.

Formally, given a tail entity \( t \) and its vector \( e_t \), and the semantic vectors of the candidate mentions \( E_t = (e_t^1, e_t^2, \ldots, e_t^n) \), \( E_t \) denotes the candidate mention set, \( E^+ \) denotes a candidate mention vector for the entity \( t \). All the semantic vectors are calculated by Word2Vec, and then we can obtain the probabilities for the candidate mentions, which are calculated by the following formulas:

\[
\begin{align*}
    d_i &= ||e_t^i - e_t|| \\ 
    scores &= \text{softmax}(d_1, d_2, \ldots, d_n) \\ 
    P_i &= scores(i)
\end{align*}
\]

where \( d_i \) denotes the semantic distance between the \( i \)-th candidate mention and the original mention, \( scores \) is the probabilities to be chosen for every mention in \( E^+ \), \( P_i \) denotes the probability of the \( i \)-th mention to be chosen.

After replacing and encoding, we can obtain the final word token representations for the head entity and relation for the factual knowledge, then we apply mean pooling operation over the consecutive tokens that mention the head entity and relation, we simply concatenate the head entity and relation representations and add a Linear Layer for prediction.

### 3.5.2 Fact-based Replacement

The second stage is to explore fact-based replacement, which helps to extend the knowledge range by injecting them to the word representation model. Generally, given a sentence the model can only learn the fact knowledge contained in the sentence; however, the similar facts cannot be learned. In the fact-replacement stage, we replace the fact unit based on the domain-specific professional knowledge base and operational rules. We consider the fact conforms to the professional knowledge and operational rules as positive and others as negative. This task aims to
predict whether the knowledge is true after a fact unit is replaced, the whole procedure is depicted in Figure 6.

![Figure 6: Fact-based entity replacement procedure.](image)

We first analyze the factual knowledge within the input sentences, then we apply knowledge parser module to convert the factual knowledge to machine readable ones. Next, we use reasoning machine, using domain knowledge base as well as operational rules as knowledge source, to perform knowledge inference. To guarantee the correctness of inferred knowledge, we add a knowledge check module which takes the output of the reasoning machine as input, to verify the inferred knowledge, as a result, we can obtain the positive knowledge set, and the negative samples. Considering the possibility of introducing knowledge noise, the ratio of positive to negative samples is controlled at 1:2.

To construct the positive factual knowledge set and the negative knowledge set, we first analyze the factual knowledge within the input sequence, and then use knowledge parser module to convert it to the machine reading knowledge, which always be a SQL statement or graph query language. The reasoning machine is used to produce corresponding factual knowledge, which takes the converted factual knowledge as input as well as the military knowledge bases and operational rules. To guarantee that the produced factual knowledge is ground-truth, we add a knowledge check module after the reasoning machine. With these modules, we can obtain the positive factual knowledge set for knowledge replacement, and the negative set consists of random samples that is not contained in the positive set. We replace the origin knowledge with (1) a random from the positive set in 50% time, (2) a random from the negative set in 50% time.

After two stage entity replacement, domain-specific prior knowledge is incorporated into the model, and then a knowledge enhanced language representation model with richer domain-specific knowledge is obtained.

### 3.6 Pre-training Details

In pre-training procedure, we follow ERNIE 2.0 (Sun et al., 2020) and apply a continual multi-task learning strategy to train MLRIP. As described in Section 3.2, we use multi-layer Transformer as basic encoder, and the model configuration is the same as BERTbase. Meanwhile, most of the hyper-parameters configuration is the same as it, except for batch size, learning rate and max sequence length. We set the max sequence as 256 and double the batch size up to 512 to accelerate the training process. We adopt Adam as optimizer, set the learning rate to 3e-5, L2 weight decay to 1e-3, learning rate warm up for the first 20% steps, and then linearly decay the learning rate. We train MLRIP with 8 NVIDIA Tesla V100 (32G) GPUs.

### 4 Experiments

#### 4.1 Data Feature Analysis and Data Preparation

Pre-trained language models have achieved significant performance improvements on various downstream NLP tasks by training them on large and multi-source heterogeneous data. In this proposed work, we choose five categories of professional data, namely operational documents, intelligence documents, military scenarios, military books and military simulation system logs, and seven categories of network data, namely military website documents, military game strategies, military news, military comments, military blogs, military forum data, and Chinese Wikipedia as our training corpora. We have analyzed and categorized this data in detail in our previous work (Li et al., 2022), and refer readers to that work for the data information. Our previous work shows that the word distributions are quite different in different data source texts, for example, military terms are mostly expressed in formal or standard expressions in military scenarios, military books, while military terms are dominated by abbreviations and code names in military intelligence texts.

To the best of our knowledge, there are no publicly available datasets for military NLP tasks in the military domain. Therefore, we construct various benchmark datasets from a wide range of multi-source heterogeneous military texts for military word representation language model performance evaluation.

Following GLUE (Wang et al., 2018), SQuAD (Rajpurkar et al., 2016), CoNLL-2012 (Pradhan et al., 2012), and FIGER (Ling and Weld, 2012), we construct three benchmark datasets, a fine-grained military entity typing dataset (FGMET), a military named entity recognition dataset (MNER), and a large-scale complex relation extraction corpus for military domain (LCRECM). As how to construct the benchmarks is out of the topic of this issue, we only
present the statistic information about all the benchmarks. The statistic information for each benchmark is shown in Table 1, Table 2 and Table 3. Each of the dataset is divided into three parts: train, development, and test. The train part is used to fine-tune the model and then its performance is evaluated on the development and test parts.

| Dataset       | Train   | Develop | Test   | Type |
|---------------|---------|---------|--------|------|
| FGMET         | 256,000 | 32,000  | 32,000 | 71   |

Table 2: The statistic of the military entity recognition dataset MNER.

| Dataset       | Train   | Develop | Test   | Type |
|---------------|---------|---------|--------|------|
| MNER          | 24,960  | 3,120   | 3,120  | 12   |

Table 3: The statistic of the large-scale complex relation extraction corpus for military domain LCRECM.

| Dataset       | Train       | Develop    | Test    | Type  |
|---------------|-------------|------------|---------|-------|
| LCRECM        | 61,458      | 21,098     | 15,280  | 132   |

4.2 Experiments on Military NLP Tasks

We evaluate on a comprehensive suite of military NLP tasks, including entity typing, military NER, and relation extraction.

4.2.1 Military NER

NER is a fundamental military text mining task, usually performed for constructing knowledge base, operational planning, situational analysis, etc., and this task is always taken as a sequence labeling task. In this study, we use MNER dataset, covering 12 kinds and 16,729 military entities, to evaluate our model with the baselines, and choose Precision, Recall, and F1 as metrics.

4.2.2 Entity Typing

The task of entity typing aims to predict the semantic types of a given entity in the military text, which is a principal task in intelligence knowledge mining. To evaluate the performance on this task, we fine-tune our model on FGMET, which is a well-established and fine-grained military entity typing dataset, covering 71 kinds of military entities. In the fine-tuning procedure, sentences with military entity mentions are fed into the MLRIP, then we obtain the entity types. We evaluate the models with metrics of micro and macro F1 scores and compare our model with the baseline models for entity typing.

4.2.3 Relation Extraction

Military entity relation extraction is a challenging work as the relation between every two given entities may be multiple or be expressed with different forms. To evaluate performance on this task, we perform fine-tune our model on LCRECM, and compare it with baselines.

4.3 Baselines

As we mainly concern the performance improvements over BERT and knowledge enhanced models which use BERT as backbone, thus we compare our model with the following BERT or BERT-based models. We implemented these models by using the HuggingFace Transformers (Wolf et al., 2019).

- BERT
- ERNIE-Baidu-military (MERNIE)

4.4 Experimental Result Analysis

In this section, we present the experimental results on two knowledge-driven tasks, and military NER task.

4.4.1 Military NER

Table 4 shows the performance on MNER benchmark. We have the following observations: (1) Compared to BERT, MERNIE achieves a F1 score increase of 0.44%, indicating that incorporating external knowledge into language representation model benifits mil-

| Model      | P    | R    | F1   |
|------------|------|------|------|
| BERT       | 54.82| 58.45| 56.16|
| MERNIE     | 55.59| 59.27| 56.60|
| MLRIP      | 55.89| 59.73| 57.46|

4.4.2 Entity Typing

Table 5 presents the performance on entity typing dataset FGMET. We can observe that: (1) MERNIE achieves higher performance than BERT, improving macro-F1 by 1.95% and micro-F1 by 1.11%, which means that knowledge masking strategy helps to learn more information about entity. (2) MLRIP
outperforms baselines and achieves the state-of-the-art performance, which demonstrates the pre-training strategies proposed in this work benefit entity typing.

Table 5: Results on entity typing dataset FGMET.

| Model   | Macro-F1 | Micro-F1 |
|---------|----------|----------|
| BERT    | 70.05    | 77.61    |
| MERNIE  | 72.00    | 78.72    |
| MLRIP   | 76.51    | 79.50    |

4.4.3 Relation Extraction

Table 6 shows the performance on relation extraction benchmark. We can observe that: (1) MLRIP significantly outperforms the baselines on RE task, (2) BERT outperforms MERNIE, we argue that the sequential multi-task learning tends to forget some knowledge it has learnt and the continual multi-task learning helps to obtain better performance on downstream tasks without any efficiency sacrifice.

Table 6: Results on military entity relation extraction dataset LCRECM.

| Model   | P       | R       | F1     |
|---------|---------|---------|--------|
| BERT    | 47.68   | 48.54   | 44.52  |
| MERNIE  | 44.46   | 41.87   | 40.51  |
| MLRIP   | 55.12   | 51.52   | 50.26  |

5 Ablation

In order to analyze the effectiveness of the strategies adopted in our work, we perform ablation experiments over every strategy of the MLRIP to study the impact of them in this section.

We perform ablation studies over every strategies of MLRIP with FGMET benchmark. ERNIE-Baidu (Sun et al., 2019) has proven the effectiveness of phrase-level masking and entity-level masking strategies, as MLRIP also use the phrase-level and entity-level masking strategies but it modifies the entity-level masking strategy by adding FKP, so we apply MERNIE as baseline named MLRIP\textsubscript{base}. We explore the effectiveness for the remaining strategies based on this baseline. \& rel\_ent\_mask refers to add entity-level masking (add FKP strategy) and relation-level masking strategies, as both these two strategies can be pre-trained together so we can take these two strategy as one strategy and report their experimental result. \& ment\_ent\_rep refers to add same entity mention replacement strategy, and add fact-based replacement strategy. Table 7 presents the ablation experimental results, from which we can see that: (1) the performance on FGMET can be improved by every strategy proposed in this paper, (2) Entity replace strategy outperforms entity-level masking and relation-level masking strategy, since that the entity replacement strategy helps to inject more external prior knowledge about the entities to the language representation model, (3) with all these strategies applied the performance is further promoted.

Table 7: Ablation experimental results on FGMET.

| Model     | Macro-F1 | Micro-F1 |
|-----------|----------|----------|
| MLRIP\textsubscript{base} | 72.00    | 78.72    |
| \& rel\_ent\_mask | 75.08    | 78.93    |
| \& ment\_ent\_rep | 75.81    | 79.08    |
| MLRIP     | 76.51    | 79.50    |

6 Conclusion

In this paper, we propose a pre-training language representation model for military text mining, which modifies the knowledge integration strategy proposed by Sun et al. (2019), and introduce a novel two stage entity replacement strategy to incorporate external prior knowledge into pre-trained models. Experimental results on knowledge-driven military NLP tasks demonstrate that our method MLRIP outperforms BERT-based models over all the tasks. To verify the effectiveness of our proposed strategies, we perform ablation studies on all of them. The ablation experimental results show that our strategies achieve improvement individually, and benefit military text mining.

In future work, we will explore more pre-training tasks to integrate domain-specific knowledge into context-sense representation models, such as special-token prediction, or sentiment analysis task. In addition, we will also explore infuse more types of knowledge and apply other language representation to validate our idea.

References

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. arXiv preprint arXiv:1802.05365, 2018.

Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

Anthi Symeonidou, Viachaslau Sazonau, and Paul Groth. Transfer learning for biomedical named entity recognition with biobert. In SEMANTICS Posters & Demos, 2019.
Dogu Araci. Finbert: Financial sentiment analysis with pre-trained language models. *arXiv preprint arXiv:1908.10063*, 2019.

Iz Beltagy, Kyle Lo, and Arman Cohan. Scibert: A pretrained language model for scientific text. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3615–3620. Association for Computational Linguistics, 2019.

Jieh-Sheng Lee and Jieh Hsiang. Patent classification by fine-tuning bert language model. *World Patent Information*, 61:101965, 2020.

Wenhan Xiong, Jingfei Du, William Yang Wang, and Veselin Stoyanov. Pretrained encyclopedia: Weakly supervised knowledge-pretrained language model. *arXiv preprint arXiv:1912.09637*, 2019.

Bin He, Di Zhou, Jinghui Xiao, Qin Liu, Nicholas Jing Yuan, Tong Xu, et al. Integrating graph contextualized knowledge into pre-trained language models. *arXiv preprint arXiv:1912.00147*, 2019.

Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Asli Celikyilmaz, and Yejin Choi. Comet: Commonsense transformers for automatic knowledge graph construction. *arXiv preprint arXiv:1906.05317*, 2019.

Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Xuyi Han, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. Ernie: Enhanced representation through knowledge integration. *arXiv preprint arXiv:1904.09223*, 2019.

Zhengyan Zhang, Xu Han, Zhiyuan Liu, Xin Jiang, Maosong Sun, and Qin Liu. ERNIE: Enhanced Language Representation with Informative Entities. In *57th Annual Meeting of the Association for Computational Linguistics (Acl 2019)*, pages 1441–1451, 2019.

Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanjing Huang, Guihong Cao, Daxin Jiang, Ming Zhou, et al. K-adapter: Infusing knowledge into pre-trained models with adapters. *arXiv preprint arXiv:2002.01808*, 2020.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. XLNet: Generalized Autoregressive Pretraining for Language Understanding. In *33rd Conference on Neural Information Processing Systems (NeurIPS 2019)*, volume 32, 2019.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. Spanbert: Improving pre-training by representing and predicting spans. *Transactions of the Association for Computational Linguistics*, 8:64–77, 2020.

Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, and Zaqing Yang. Pre-training with whole word masking for chinese bert. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3504–3514, 2021.

Xiao Liu, Da Yin, Xingjian Zhang, Kai Su, Kan Wu, Hongxia Yang, and Jie Tang. Oag-bert: Pre-train heterogeneous entity-augmented academic language models. *arXiv preprint arXiv:2103.02410*, 2021.

Yujia Qin, Yankai Lin, Ryuichi Takano, Zhiyuan Liu, Peng Li, Heng Ji, Minlie Huang, Maosong Sun, and Jie Zhou. Erica: improving entity and relation understanding for pre-trained language models via contrastive learning. *arXiv preprint arXiv:2012.15022*, 2020.

Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Hua Wu, and Haifeng Wang. Ernie 2.0: A continual pre-training framework for language understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8968–8975, 2020.

Hui Li, Lin Yu, Jie Zhang, and Ming Lyu. Fusion deep learning and machine learning for heterogeneous military entity recognition. *Wireless Communications and Mobile Computing*, 2022, 2022.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355. Association for Computational Linguistics, 2018.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*, 2016.
Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Olga Uryupina, and Yuchen Zhang. Conll-2012 shared task: Modeling multilingual unrestricted coreference in ontonotes. In Joint Conference on EMNLP and CoNLL-Shared Task, pages 1–40, 2012.

Xiao Ling and Daniel S Weld. Fine-grained entity recognition. In Twenty-Sixth AAAI Conference on Artificial Intelligence, 2012.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, and Morgan and Funtowicz. Huggingface’s transformers: State-of-the-art natural language processing. arXiv preprint arXiv:1910.03771, 2019.