ERNIE-Gram: Pre-Training with Explicitly N-Gram Masked Language Modeling for Natural Language Understanding

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Abstract

Coarse-grained linguistic information, such as name entities or phrases, facilitates adequately representation learning in pre-training. Previous works mainly focus on extending the objective of BERT's Masked Language Modeling (MLM) from masking individual tokens to contiguous sequences of n tokens. We argue that such continuously masking method neglects to model the inner-dependencies and inter-relation of coarse-grained information. As an alternative, we propose ERNIE-Gram, an explicitly n-gram masking method to enhance the integration of coarse-grained information for pre-training. In ERNIE-Gram, n-grams are masked and predicted directly using explicit n-gram identities rather than contiguous sequences of tokens. Furthermore, ERNIE-Gram employs a generator model to sample plausible n-gram identities as optional n-gram masks and predict them in both coarse-grained and fine-grained manners to enable comprehensive n-gram prediction and relation modeling. We pre-train ERNIE-Gram on English and Chinese text corpora and fine-tune on 19 downstream tasks. Experimental results show that ERNIE-Gram outperforms previous pre-training models like XLNet and RoBERTa by a large margin, and achieves comparable results with state-of-the-art methods.

1 Introduction

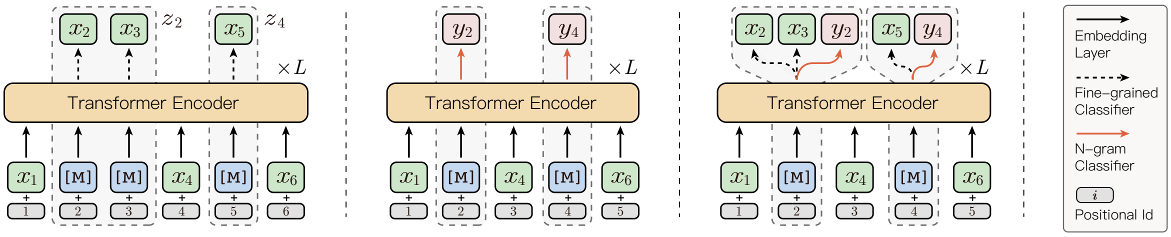
Pre-trained on large-scaled text corpora and fine-tuned on downstream tasks, self-supervised representation models ((Radford et al., 2018; Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019; Lan et al., 2019; Clark et al., 2020)) have achieved remarkable improvements in natural language understanding (NLU). As one of the most prominent pre-trained models, BERT (Devlin et al., 2019) employs masked language modeling (MLM) to learn representations by masking individual tokens and predicting them based on their bidirectional context. However, BERT's MLM focuses on the representations of fine-grained text units (e.g. words or subwords in English and characters in Chinese), rarely considering the coarse-grained linguistic information (e.g. named entities or phrases in English and words in Chinese) thus incurring inadequate representation learning.

Many efforts have been devoted to integrate coarse-grained semantic information by independently masking and predicting contiguous sequences of n tokens, namely n-grams, such as named entities, phrases (Sun et al., 2019b), whole words (Cui et al., 2019) and text spans (Joshi et al., 2019). We argue that such continuously masking strategies are less effective and reliable since the prediction of tokens in masked n-grams are independent of each other, which neglects the inner dependencies of n-grams. Specifically, given a masked n-gram $\boldsymbol{w}=\{x_1, ..., x_n\}, x \in \mathcal{V}_F$, we maximize $p(\boldsymbol{w})=\prod_{i=1}^{n} p(x_i|\boldsymbol{c})$ to train the model predicting the correct $\boldsymbol{w}$ in a huge and sparse prediction space $\mathcal{F} \in \mathbb{R}^{|\mathcal{V}_F|^n}$, where $\mathcal{V}_F$ is the fine-grained vocabulary[1] and $\boldsymbol{c}$ is the context.

We propose ERNIE-Gram, an **explicitly n-gram masked** language modeling method in which n-grams are masked with single `[MASK]` symbols, and then predicted directly using explicit n-gram identities rather than sequences of tokens, as depicted in Figure 1b. The models learn to predict n-gram $\boldsymbol{w}$ in a small and dense prediction space $\mathcal{N} \in \mathbb{R}^{|\mathcal{V}_N|}$, where $\mathcal{V}_N$ indicates a prior n-grams lexicon[2] and normally $|\mathcal{V}_N| \ll |\mathcal{V}_F|^n$. To further model the inner dependencies of semantic n-grams, we adopt a **comprehensive n-gram prediction** mechanism, simultaneously predicting masked n-grams in coarse-grained (explicit n-gram

[1] $\mathcal{V}_F$ contains 30K BPE codes in BERT and 50K subword units in RoBERTa (Liu et al., 2019)

[2] $\mathcal{V}_N$ contains 300K n-grams and $n \in [2, 4)$ in this paper.



(a) Continuously N-gram MLM (b) Explicitly N-gram MLM (c) Comprehensive N-gram MLM

Figure 1: Illustrations of different MLM objectives, where x_i and y_i represent the identities of fine-grained tokens and explicit n-grams respectively. Note that the weights of fine-grained classifier ($W_F \in \mathbb{R}^{h\times|\mathcal{V}_F|}$) and N-gram classifier ($W_N \in \mathbb{R}^{h\times|\langle\mathcal{V}_F,\mathcal{V}_N\rangle|}$) are not used in fine-tuning stage, where h is the hidden size and L is the layers.

identities) and fine-grained (contained token identities) manners with well-designed attention mask metrics, as shown in Figure 1c.

In addition, to model the semantic relationships between n-grams directly, we introduce an **enhanced n-gram relation modeling** mechanism, masking n-grams with plausible n-grams identities sampled from a generator model, and then recovering them to the original n-grams with the pair relation between plausible and original n-grams. Inspired by ELECTRA (Clark et al., 2020), we incorporate the replaced token detection objective to distinguish original n-grams from plausible ones, which enhances the interactions between explicit n-grams and fine-grained contextual tokens.

In this paper, we pre-train ERNIE-Gram on both base-scale and large-scale text corpora (16GB and 160GB respectively) under comparable pre-training setting. Then we fine-tune ERNIE-Gram on 13 English NLU tasks and 6 Chinese NLU tasks. Experimental results show that ERNIE-Gram consistently outperforms previous well-performed pre-training models on various benchmarks by a large margin.

2 Related Work

2.1 Self-Supervised Pre-Training for NLU

Self-supervised pre-training has been used to learn contextualized sentence representations though various training objectives. GPT (Radford et al., 2018) employs unidirectional language modeling (LM) to exploit large-scale corpora. BERT (Devlin et al., 2019) proposes masked language modeling (MLM) to learn bidirectional representations efficiently, which is a representative objective for pre-training and has numerous extensions such as RoBERTa (Liu et al., 2019), UniLM (Dong et al., 2019) and ALBERT (Lan et al., 2019). XLNet (Yang et al., 2019) adopts permutation language modeling (PLM) to model the dependencies among predicted tokens. ELECTRA introduces replaced token detection (RTD) objective to learn all tokens for more compute-efficient pre-training.

2.2 Coarse-grained Linguistic Information Incorporating for Pre-Training

Coarse-grained linguistic information is indispensable for adequate representation learning. There are lots of studies that implicitly integrate coarse-grained information by extending BERT's MLM to continuously masking and predicting contiguous sequences of tokens. For example, ERNIE (Sun et al., 2019b) masks named entities and phrases to enhance contextual representations, BERT-wwm (Cui et al., 2019) masks whole Chinese words to achieve better Chinese representations, SpanBERT (Joshi et al., 2019) masks contiguous spans to improve the performance on span selection tasks.

A few studies attempt to inject the coarse-grained n-gram representations into fine-grained contextualized representations explicitly, such as ZEN (Diao et al., 2019) and AMBERT (Zhang and Li, 2020), in which additional transformer encoders and computations for explicit n-gram representations are incorporated into both pre-training and fine-tuning. Li et al., 2019 demonstrate that explicit n-gram representations are not sufficiently reliable for NLP tasks because of n-gram data sparsity and the ubiquity of out-of-vocabulary n-grams. Differently, we only incorporate n-gram information by leveraging auxiliary n-gram classifier and embedding weights in pre-training, which will be completely removed during fine-tuning, so our method maintains the same parameters and computations as BERT.

3 Proposed Method

In this section, we present the detailed implementation of ERNIE-Gram, including n-gram lexicon

$\mathcal{V}_N$ extraction in Section 3.1, explicitly n-gram MLM pre-training objective in Section 3.2, comprehensive n-gram prediction and relation modeling mechanisms in Section 3.3 and 3.4.

3.1 N-gram Extraction

N-gram Lexicon Extraction. We employ T-test to extract semantically-complete n-grams statistically from unlabeled text corpora $\mathcal{X}$ (Xiao et al., 2020), as described in Algorithm 1. We first calculate the t-statistic scores of all n-grams appearing in $\mathcal{X}$ since the higher the t-statistic score, the more likely it is a semantically-complete n-gram. Then, we select the l-grams with the top k_l t-statistic scores to construct the final n-gram lexicon $\mathcal{V}_N$.

N-gram Boundary Extraction. To incorporate n-gram information into MLM objective, n-gram boundaries are referred to mask whole n-grams for pre-training. Given an input sequence $\boldsymbol{x} = \{x_1, ..., x_{|\boldsymbol{x}|}\}$, we traverse all possible valid n-gram paths $\mathcal{B} = \{\boldsymbol{b}_1, ..., \boldsymbol{b}_{|\mathcal{B}|}\}$ according to $\mathcal{V}_N$, then select the shortest paths as the final n-gram boundaries $\boldsymbol{b}$, where $|\boldsymbol{b}| \leq |\boldsymbol{b}_i|, \forall i = 1, ..., |\mathcal{B}|$.

Algorithm 1 N-gram Extraction with T-test

```
Input: Large-scale text corpora $\mathcal{X}$ for pre-training
Output: Semantic $n$-gram lexicon $\mathcal{V}_N$
▷ given initial hypothesis $H_0$: a randomly constructed $n$-gram $\boldsymbol{w} = \{x_1, ..., x_n\}$ with probability $p'(\boldsymbol{w}) = \prod_{i=1}^{n} p(x_i)$ cannot be a statistically semantic $n$-gram
for $l$ in range(2, $n$) do
    $\mathcal{V}_{N_l} \leftarrow \langle\rangle$    ▷ initialize the lexicon for $l$-grams
    for $l$-gram $\boldsymbol{w}$ in $\mathcal{X}$ do
        $s \leftarrow \frac{(p(\boldsymbol{w})-p'(\boldsymbol{w}))}{\sqrt{\sigma^2/N_l}}$: $t$-statistic score    ▷ where statistical probability $p(\boldsymbol{w}) = \frac{\texttt{Count}(\boldsymbol{w})}{N_l}$, deviation $\sigma^2 = p(\boldsymbol{w})(1-p(\boldsymbol{w}))$, $N_l$ donates the count of $l$-grams in $\mathcal{X}$
        $\mathcal{V}_{N_l}$.append($\{\boldsymbol{w}, s\}$)
    $\mathcal{V}_{N_l} \leftarrow$ topk($\mathcal{V}_{N_l}, k_l$)    ▷ $k_l$ is the number of $l$-gram
$\mathcal{V}_N \leftarrow \langle\mathcal{V}_{N_2}, ..., \mathcal{V}_{N_n}\rangle$    ▷ merge all lexicons
return $\mathcal{V}_N$
```

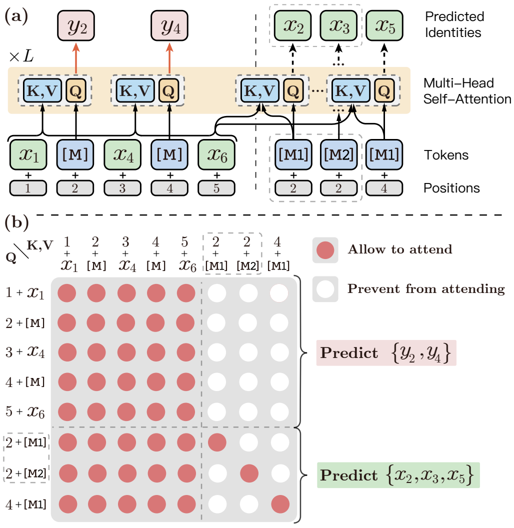


Figure 2: (a) Detailed structure of Comprehensive N-gram MLM. (b) Self-attention mask M without leaking length information of masked n-grams.

3.2 Explicitly N-gram Masked Language Modeling

Contiguously N-gram MLM. Given input sequence $\boldsymbol{x}=\{x_1, ..., x_{|\boldsymbol{x}|}\}, x \in \mathcal{V}_F$ and corresponding n-gram boundaries $\boldsymbol{b} = \{b_1, ..., b_{|\boldsymbol{b}|}\}$, let $\boldsymbol{z} = \{z_1, ..., z_{|\boldsymbol{b}|}\}$ to be the sequence of n-grams, where $z_i = \boldsymbol{x}_{b_i:b_{i+1}}$, MLM samples 15% of starting boundaries from $\boldsymbol{b}$ to mask n-grams, donating $\mathcal{M}$ as the indexes of sampled starting boundaries, $\boldsymbol{z}_{\mathcal{M}}$ as the continuously masked tokens, $\boldsymbol{z}_{\setminus\mathcal{M}}$ as the sequence after masking. As shown in Figure 1a, $\boldsymbol{b} = \{1, 2, 4, 5, 6\}$, $\boldsymbol{z} = \{x_1, \boldsymbol{x}_{2:3}, x_4, x_5, x_6\}$, $\mathcal{M} = \{2, 4\}$, $\boldsymbol{z}_{\mathcal{M}} = \{\boldsymbol{x}_{2:3}, x_5\}$, and $\boldsymbol{z}_{\setminus\mathcal{M}} = \{x_1, \texttt{[M]}, \texttt{[M]}, x_4, \texttt{[M]}, x_6\}$. Contiguously n-gram MLM is performed by minimizing the negative likelihood:

$$-\log p_\theta(\boldsymbol{z}_{\mathcal{M}}|\boldsymbol{z}_{\setminus\mathcal{M}}) = -\sum_{z \in \boldsymbol{z}_{\mathcal{M}}} \sum_{x \in z} \log p_\theta(x|\boldsymbol{z}_{\setminus\mathcal{M}}). \quad (1)$$

Explicitly N-gram MLM. Different from contiguously n-gram MLM, we employ explicit n-gram identities as pre-training targets to reduce the prediction space for n-grams. To be specific, let $\boldsymbol{y} = \{y_1, ..., y_{|\boldsymbol{b}|}\}, y \in \langle\mathcal{V}_F, \mathcal{V}_N\rangle$ to be the sequence of explicit n-gram identities, $\boldsymbol{y}_{\mathcal{M}}$ to be the target n-gram identities, and $\bar{\boldsymbol{z}}_{\setminus\mathcal{M}}$ to be the sequence after explicitly masking n-grams. As shown in Figure 1b, $\boldsymbol{y}_{\mathcal{M}} = \{y_2, y_4\}$, and $\bar{\boldsymbol{z}}_{\setminus\mathcal{M}} = \{x_1, \texttt{[M]}, x_4, \texttt{[M]}, x_6\}$. For masked n-gram $\boldsymbol{x}_{2:3}$, the prediction space is significantly reduced from $\mathbb{R}^{|\mathcal{V}_F|^2}$ to $\mathbb{R}^{|\langle\mathcal{V}_F, \mathcal{V}_N\rangle|}$. Explicitly n-gram MLM is performed by minimizing the negative likelihood:

$$-\log p_\theta(\boldsymbol{y}_{\mathcal{M}}|\bar{\boldsymbol{z}}_{\setminus\mathcal{M}}) = -\sum_{y \in \boldsymbol{y}_{\mathcal{M}}} \log p_\theta(y|\bar{\boldsymbol{z}}_{\setminus\mathcal{M}}). \quad (2)$$

3.3 Comprehensive N-gram Prediction

We propose to jointly predict n-grams in fine-grained and coarse-grained manners corresponding to single mask symbol `[M]`, which helps to extract comprehensive n-gram semantics, as shown

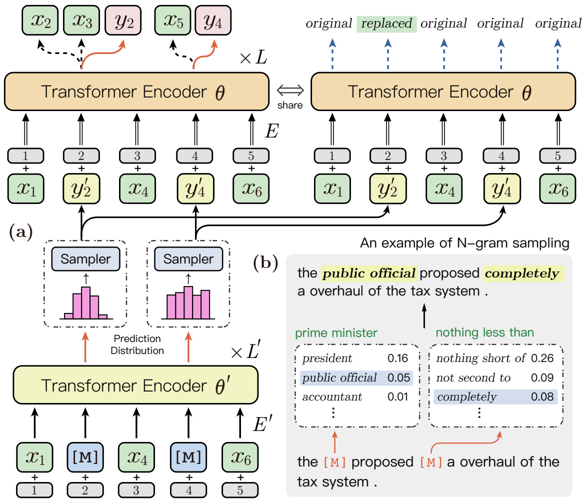


Figure 3: (a) Detailed architecture of n-gram relation modeling, where L' donates the layers of the generator model. (b) An example of plausible n-gram sampling, where dotted boxes represent the sampling module, texts in green are the original n-grams, and the italic texts in blue donate the sampled n-grams.

in Figure 1c. To predict all tokens contained in a n-gram from single `[M]` other than a consecutive sequence of `[M]`, we adopt distinctive mask symbols `[Mi]`, `i`$=1,...,n$ to aggregate contextualized representations for predicting the i-th token in n-gram. As shown in Figure 2a, along with the same position as y_2, symbols `[M1]` and `[M2]` are used to aggregate representations of $\bar{z}_{\setminus\mathcal{M}}$ for the predictions of x_2 and x_3. Note that Q, K and V donate the query, key and value in self-attention operation (Vaswani et al., 2017). As shown in Figure 2b, the self-attention mask metric M controls what context a token can attend to by modifying the attention weight $W_A = \texttt{softmax}(\frac{QK^T}{\sqrt{d_k}} + M)$, M is assigned as:

$$M_{ij} = \begin{cases} 0, & \text{allow to attended} \\ -\infty, & \text{prevent from attending} \end{cases} \quad (3)$$

We argue that the length information of n-grams is detrimental to the representations learning, because it will arbitrarily prune a number of semantically related n-grams with different lengths during predicting. From this viewpoint, for the predictions of n-gram $\{x_2, x_3\}$, 1) we prevent context $\bar{z}_{\setminus\mathcal{M}}$ from attending to $\{$`[M1]`,`[M2]`$\}$ and 2) prevent $\{$`[M1]`,`[M2]`$\}$ from attending to each other, so that the length information of n-grams will not be leaked in pre-training, as displayed in Figure 2b. Comprehensive n-gram MLM is performed by minimizing the likelihood:

$$-\log p_\theta(\boldsymbol{y}_\mathcal{M}, \boldsymbol{z}_\mathcal{M}|\bar{z}_{\setminus\mathcal{M}}) = -\sum_{y\in\boldsymbol{y}_\mathcal{M}} \log p_\theta(y|\bar{z}_{\setminus\mathcal{M}}) - \sum_{z\in\boldsymbol{z}_\mathcal{M}}\sum_{x\in z} \log p_\theta(x|\bar{z}_{\setminus\mathcal{M}}). \quad (4)$$

where the predictions of explicit n-gram $\boldsymbol{y}_\mathcal{M}$ and fine-grained tokens $\boldsymbol{x}_\mathcal{M}$ are conditioned on the same context sequence $\bar{z}_{\setminus\mathcal{M}}$.

3.4 Enhanced N-gram Relation Modeling

To explicitly learn the semantic relationships between n-grams, we jointly pre-train a small generator model θ' with explicitly n-gram MLM objective to sample plausible n-gram identities. Then we employ the generated identities to preform masking and train the standard model θ to predict the original n-grams from fake ones in coarse-grained and fine-grained manners, as shown in Figure 3a, which is efficient to model the pair relationships between similar n-grams.

As shown in Figure 3b, n-grams of different length can be sampled to mask original n-grams according to the prediction distributions, which is more flexible and sufficient for constructing n-gram pairs than previous synonym masking methods (Cui et al., 2020) that require synonyms and original words to be of the same length. Notice that our method needs a large embedding layer $E \in \mathbb{R}^{|\langle\mathcal{V}_F,\mathcal{V}_N\rangle|\times h}$ to obtain n-gram vectors in pre-training. To keep the number of parameters consistent with that of vanilla BERT, we remove the embedding weights of n-grams during fine-tuning ($E \rightarrow E' \in \mathbb{R}^{|\mathcal{V}_F|\times h}$). Specifically, let $\boldsymbol{y}'_\mathcal{M}$ to be the generated n-gram identities, $\bar{z}'_\mathcal{M}$ to be the sequence masked by $\boldsymbol{y}'_\mathcal{M}$, where $\boldsymbol{y}'_\mathcal{M} = \{y'_2, y'_4\}$, and $\bar{z}'_{\setminus\mathcal{M}} = \{x_1, y'_2, x_4, y'_4, x_6\}$ in Figure 3(a). The pre-training objective is to minimize the jointly negative likelihood of θ' and θ:

$$-\log p_{\theta'}(\boldsymbol{y}_\mathcal{M}|\bar{z}_{\setminus\mathcal{M}}) - \log p_\theta(\boldsymbol{y}_\mathcal{M}, \boldsymbol{z}_\mathcal{M}|\bar{z}'_{\setminus\mathcal{M}}). \quad (5)$$

Moreover, we incorporate the replaced token detection objective (RTD) to further distinguish fake n-grams from the mix-grained context $\bar{z}'_{\setminus\mathcal{M}}$ for interactions among explicit n-grams and fine-grained contextual tokens, as shown in the right part of Figure 3a. Formally, we donate $\hat{z}_{\setminus\mathcal{M}}$ to be the sequence after replacing masked n-grams with target n-gram identities $\boldsymbol{y}_\mathcal{M}$, the RTD objective is performed by minimizing the negative likelihood:

$$\begin{aligned} & -\log p_\theta\big(\mathbb{1}(\bar{\boldsymbol{z}}'_{\setminus\mathcal{M}} = \hat{\boldsymbol{z}}_{\setminus\mathcal{M}})|\bar{\boldsymbol{z}}'_{\setminus\mathcal{M}}\big) \\ & = -\sum_{t=1}^{|\hat{\boldsymbol{z}}_{\setminus\mathcal{M}}|} \log p_\theta\big(\mathbb{1}(\bar{\boldsymbol{z}}'_{\setminus\mathcal{M},t} = \hat{\boldsymbol{z}}_{\setminus\mathcal{M},t})|\bar{\boldsymbol{z}}'_{\setminus\mathcal{M}}, t\big). \end{aligned} \tag{6}$$

As the example in Figure 3a depicts, the target context sequence $\hat{\boldsymbol{z}}_{\setminus\mathcal{M}} = \{x_1, y_2, x_4, y_4, x_6\}$.

4 Experiments

In this section, we first present the pre-training configuration of ERNIE-Gram on Chinese and English text corpora. Then we compare the fine-tuning results of ERNIE-Gram with previous works on various NLU tasks. We also conduct several ablation experiments to access the major components of ERNIE-Gram.

4.1 Pre-training Text Corpora

English Pre-training Data. We use two common text corpora for English pre-training:

- **Base-scale corpora:** 16GB uncompressed text from WIKIPEDIA and BOOKSCORPUS (Zhu et al., 2015), which is the original data for BERT.
- **Large-scale corpora:** 160GB uncompressed text from WIKIPEDIA, BOOKSCORPUS, OPEN-WEBTEXT[3], CC-NEWS (Liu et al., 2019) and STORIES (Trinh and Le, 2018), which is the original data used in RoBERTa.

Chinese Pre-training Data. We adopt the same Chinese text corpora used in ERNIE2.0 (Sun et al., 2020) to pre-train ERNIE-Gram.

4.2 Pre-training Setup

Before pre-training, we first extract 200K bi-grams and 100K tri-grams with Algorithm 1 to construct the semantic n-gram lexicon $\mathcal{V}_N$. and we adopt the sub-word dictionary (30K BPE codes) used in BERT as our fine-grained vocabulary $\mathcal{V}_F$.

Following the previous practice, we pre-train ERNIE-Gram in base size ($L = 12, H = 768$, $A = 12$, Total Parameters=110M)[4], and set the length of the sequence in each batch up to 512 tokens. We use Adam (Kingma and Ba, 2015) with $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-6}$ for optimizing. For pre-training on base-scale English corpora, the batch size is set to 256 sequences, the peak learning rate is $1e$-4 for 1M training steps, which are the same settings as BERT. As for the pre-training on large-scale English corpora (underway), the batch size is 5112 sequences, the peak learning rate is $4e$-4 for 500K steps. For pre-training on Chinese corpora, the batch size is 256 sequences, the peak learning rate is $1e$-4. All the pre-training hyper-parameters are supplemented in the Appendix A.

In fine-tuning, the embedding weights of explicit n-grams identities are removed from pre-trained models for fair comparison with previous models like BERT, RoBERTa and XLNet.

4.3 Results on Question Answering (SQuAD)

The Stanford Question Answering (SQuAD) tasks are designed to extract the answer span within the given passage conditioned on the question. We conduct experiments on SQuAD1.1 (Rajpurkar et al., 2016) and SQuAD2.0 (Rajpurkar et al., 2018) by adding a classification layer on the sequence outputs of ERNIE-Gram and predicting whether each token is the start or end position of the answer span.

Table 2 presents the results on SQuAD benchmark for base-size models. Pre-trained with base-scale text corpora, ERNIE-Gram achieves better performance than current strong baselines, i.e., MPNet and UNILMv2.

Models	**SQuAD1.1**		**SQuAD2.0**	
	EM	F1	EM	F1
*Models pre-trained on **large-scale** text corpora (160GB)*				
RoBERTa (Liu et al., 2019)	84.6	91.5	80.5	83.7
XLNet (Yang et al., 2019)	-	-	80.2	-
ELECTRA (Clark et al., 2020)	86.8	-	80.5	-
MPNet (Song et al., 2020)	86.8	92.5	82.8	85.6
UNILMv2 (Bao et al., 2020)	87.1	93.1	83.3	86.1
*Models pre-trained on **base-scale** text corpora (16GB)*				
BERT (Devlin et al., 2019)	80.8	88.5	73.7	76.3
RoBERTa (Liu et al., 2019)	-	90.6	-	79.7
XLNet (Yang et al., 2019)	-	-	78.2	81.0
MPNet (Song et al., 2020)	85.0	91.4	80.5	83.3
UNILMv2 (Bao et al., 2020)	85.6	92.0	80.9	83.6
ERNIE-Gram	**86.2**	**92.3**	**82.1**	**84.8**

Table 2: Performance comparison between base-size pre-trained models on the SQuAD development sets. Exact-Match (EM) and F1 score are adopted for evaluations. Results of ERNIE-Gram are the median of over five runs with different random seeds.

4.4 Results on GLUE Benchmark

The General Language Understanding Evaluation (GLUE; Wang et al., 2019) is a multi-task bench-

[3] http://web.archive.org/save/http://Skylion007.github.io/OpenWebTextCorpus

[4] We donate the number of layers as L, the hidden size as H and the number of self-attention heads as A.

Models	#Param	MNLI	QNLI	QQP	SST-2	CoLA	MRPC	RTE	STS-B	GLUE
		Acc	Acc	Acc	Acc	MCC	Acc	Acc	PCC	Avg
*Results of single models pre-trained on **large-scale** text corpora (160GB or more)*										
XLNet (Yang et al., 2019)	110M	86.8	91.7	91.4	94.7	60.2	88.2	74.0	89.5	84.5
RoBERTa (Liu et al., 2019)	135M	87.6	92.8	91.9	94.8	63.6	90.2	78.7	91.2	86.4
UniLMv2 (Bao et al., 2020)	110M	88.5	93.5	91.7	95.1	65.2	91.8	81.3	91.0	87.3
MPNet (Song et al., 2020)	110M	88.5	93.3	91.9	95.4	65.0	91.5	85.2	90.9	87.7
*Results of single models pre-trained on **base-scale** text corpora (16GB)*										
BERT (Devlin et al., 2019)	110M	84.5	91.7	91.3	93.2	58.9	87.3	68.6	89.5	83.1
TUPE (Ke et al., 2020)	110M	86.2	92.1	91.3	93.3	63.6	89.9	73.6	89.2	85.0
F-TFM$_{\text{ELECTRA}}$ (Dai et al., 2020)	110M	86.4	92.1	91.7	93.1	64.3	89.2	75.4	**90.8**	85.4
F-TFM$^{\text{B-6-6-6}}_{\text{ELECTRA}}$ (Dai et al., 2020)	153M	**87.4**	92.5	91.6	**94.2**	64.3	89.7	78.3	90.1	86.0
ERNIE-Gram	110M	87.1	**92.8**	**91.8**	93.2	**68.5**	**90.3**	**79.4**	90.4	**86.7**
− relative position bias	110M	86.5	92.5	91.6	93.2	68.1	**90.3**	**79.4**	90.6	86.5

Table 1: Results on the development set of the GLUE benchmark for base-size pre-trained models. Models using 16GB text corpora are all pre-trained with a batch size of 256 sequences for 1M steps. STS-B and CoLA are reported by Pearson correlation coefficient (PCC) and Matthews correlation coefficient (MCC) respectively, other tasks are reported by accuracy (Acc). Note that results of ERNIE-Gram are the median of over five runs with different random seeds. "− relative position bias" donates the ablation model without relative position bias.

Models	IMDb	AG
	Err.	Err.
*Pre-trained on **large-scale** text corpora (160GB)*		
MPNet (Song et al., 2020)	4.4	-
*Pre-trained on **base-scale** text corpora (16GB)*		
BERT (Devlin et al., 2019)	5.4	5.9
XLNet[†] (Song et al., 2020)	4.9	-
MPNet (Song et al., 2020)	4.8	-
F-TFM$^{\text{B-6-6-6}}_{\text{ELECTRA}}$ (Dai et al., 2020)	4.8	5.2
ERNIE-Gram	**4.6**	**5.0**

Table 3: Results on the IMDb and AG test sets for text classification tasks. The listed models are all in base-size and the result of XLNet is from Song et al., 2020.

Models	RACE		
	Total	High	Middle
*Pre-trained on **large-scale** text corpora (160GB)*			
MPNet (Song et al., 2020)	72.0	70.3	76.3
*Pre-trained on **base-scale** text corpora (16GB)*			
BERT (Devlin et al., 2019)	65.0	62.3	71.7
XLNet (Yang et al., 2019)	66.8	-	-
ALBERT (Lan et al., 2019)	66.0	-	-
MPNet (Song et al., 2020)	70.4	67.7	**76.8**
ERNIE-Gram	**72.7**	**68.1**	75.1

Table 4: Comparison on the test sets of RACE. "High" and "Middle" represent the evaluation sets for high schools and middle schools respectively. "Total" is the full set for RACE tasks.

mark consisting of various NLU tasks, which contains pairwise classification tasks like language inference (MNLI, RTE; (Williams et al., 2018; Dagan et al., 2006)), question answering (QNLI; Rajpurkar et al., 2016) and paraphrase detection (QQP, MRPC; Dolan and Brockett, 2005), single-sentence classification tasks including linguistic acceptability (CoLA; Warstadt et al., 2018), sentiment analysis (SST; Socher et al., 2013), and a text similarity task (STS; Cer et al., 2017).

The fine-tuning results of ERNIE-Gram and various strong baselines are presented in Table 1. For fair comparison, the listed models are all in base size and fine-tuned without any data augmentation. ERNIE-Gram with base-scale text corpora outperforms recent baseline such as TUPE and F-TFM by 1.7 and 0.7 points on average and achieves an average score increase of 0.3 over RoBERTa with large-scale text corpora, demonstrating the effectiveness of ERNIE-Gram.

4.5 Results on Text Classification Tasks

We evaluate ERNIE-Gram on two large-scale text classification tasks that involve long text and reasoning, including sentiment analysis datasets IMDb (Maas et al., 2011) and topic classification dataset AG's News (Zhang et al., 2015). The results are reported in Table 3. It shows that ERNIE-Gram outperforms previous models on tasks involving long texts and reasoning with base-scale text corpora.

4.6 Results on RACE

The ReAding Comprehension from Examinations (RACE; Lai et al., 2017) dataset collects 88k long passages from English exams at middle and high

Models	**XNLI**		**LCQMC**		**DRCD**		**CMRC2018**	**DuReader**	**M-NER**	
	Acc		Acc		EM / F1		EM / F1	EM / F1	F1	
	Dev	Test	Dev	Test	Dev	Test	Dev	Dev	Dev	Test
RoBERTa-wwn-ext$^*_{\text{LARGE}}$	82.1	81.2	90.4	87.0	89.6 / 94.8	89.6 / 94.5	68.5 / 88.4	- / -	-	-
NEZHA$_{\text{LARGE}}$ (Wei et al., 2019)	82.2	81.2	90.9	87.9	- / -	- / -	- / -	- / -	-	-
MacBERT$_{\text{LARGE}}$ (Cui et al., 2020)	82.4	81.3	90.6	87.6	91.2 / 95.6	91.7 / 95.6	70.7 / 88.9	- / -	-	-
BERT-wwn-ext$^*_{\text{BASE}}$	79.4	78.7	89.6	87.1	85.0 / 91.2	83.6 / 90.4	67.1 / 85.7	- / -	-	-
RoBERTa-wwn-ext$^*_{\text{BASE}}$	80.0	78.8	89.0	86.4	85.6 / 92.0	67.4 / 87.2	67.4 / 87.2	- / -	-	-
ZEN$_{\text{BASE}}$ (Diao et al., 2019)	80.5	79.2	90.2	88.0	- / -	- / -	- / -	- / -	-	-
NEZHA$_{\text{BASE}}$ (Wei et al., 2019)	81.4	79.3	90.0	87.4	- / -	- / -	- / -	- / -	-	-
MacBERT$_{\text{BASE}}$ (Cui et al., 2020)	79.0	78.2	89.4	87.0	88.3 / 93.5	87.9 / 93.2	69.5 / 87.7	- / -	-	-
ERNIE1.0$_{\text{BASE}}$ (Sun et al., 2019b)	79.9	78.4	89.7	87.4	84.6 / 90.9	84.0 / 90.5	65.1 / 85.1	57.9 / 72.1	95.0	93.8
ERNIE2.0$_{\text{BASE}}$ (Sun et al., 2020)	81.2	79.7	**90.9**	87.9	88.5 / 93.8	88.0 / 93.4	69.1 / 88.6	61.3 / 74.9	95.2	93.8
ERNIE-Gram$_{\text{BASE}}$	**81.8**	**81.5**	90.6	88.5	90.2 / **95.0**	**89.9 / 94.6**	**74.3 / 90.5**	**64.2** / 76.8	**96.5**	**95.3**
– relative position bias	81.7	**81.5**	**90.9**	**88.7**	**90.3 / 95.0**	89.8 / **94.6**	73.3 / 90.3	**64.2 / 76.9**	**96.5**	**95.3**

Table 5: Results on six Chinese NLU tasks for base-size pre-trained models. Results of models with asterisks "*" are from Cui et al., 2019. "– relative position bias" donates the ablation model without relative position bias. M-NER is in short for MSRA-NER dataset. "BASE" and "LARGE" donate different sizes of pre-training models.

schools, the task is to select the correct choice from four given options according to the questions and passages. Results on RACE dataset are presented in Table 4, ERNIE-Gram achieves better performance on the full set of RACE than MPNet on both base and large text corpora.

4.7 Results on Chinese NLU Tasks

We execute extensive experiments on seven Chinese language understanding tasks, including natural language inference (XNLI; Conneau et al., 2018), machine reading comprehension (CMRC2018, DRCD, DuReader; Cui et al., 2018; Shao et al., 2018; He et al., 2017), named entity recognition (MSRA-NER; Levow, 2006) and semantic similarity (LCQMC; Liu et al., 2018).

Reusults on six Chinese tasks are presented in Table 5. It is observed that ERNIE-Gram significantly outperforms previous models across tasks by a large margin, achieving new state-of-the-art results on these Chinese NLU tasks in base-size model group. ERNIE-Gram are also better than the large-size models[5] on XNLI, LCQMC and CMRC2018 datasets.

4.8 Ablation Studies

We further conduct ablation experiments to analyze the major components of ERNIE-Gram, including explicitly n-gram MLM, comprehensive n-gram prediction and enhanced n-gram interaction.

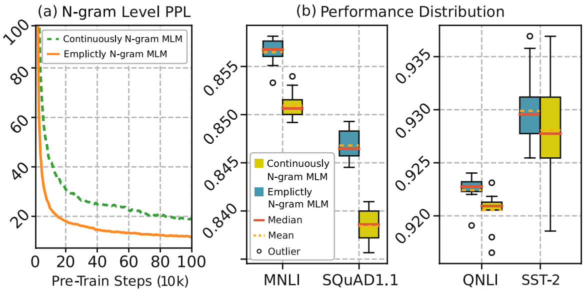


Figure 4: (a) N-gram level perplexity which is calculated by $(\prod_{i=1}^{k} \texttt{PPL}(\boldsymbol{w}_i))^{\frac{1}{k}}$, where $\boldsymbol{w}_i$ is the i-th masked n-gram. (b) Performance distribution box plot on MNLI, QNLI, SST-2 and SQuAD1.1.

Effect of Explicitly N-gram MLM. We compare two models pre-trained with contiguously n-gram MLM and explicitly n-gram MLM objectives in same settings (the size of n-gram lexicon is 300K). The evaluation results for pre-training and fine-tuning are shown in Figure 4. Compared with continuously n-gram MLM, our explicitly n-gram MLM objective facilitates the learning of n-gram semantic information with lower n-gram level perplexity in pre-training and better performance on downstream tasks. This verifies the effectiveness of explicitly n-gram MLM objective for injecting n-gram semantic information into pre-training.

Size of N-gram Lexicon. To study the impact of n-gram lexicon size on model performance, we extract n-gram lexicons with size from 10k to 40k for pre-training, as shown in Figure 5. As the lexicon size enlarges, performances of contiguously n-gram MLM become worse, presumably because more n-grams are matched and connected as longer consecutive spans for prediction, which is more difficult for representation learning. Explicitly n-

[5] $L = 24, H = 1024, A = 16$, Total Parameters=340M

#	Models	MNLI		SST-2	SQuAD1.1		SQuAD2.0	
		m	mm	Acc	EM	F1	EM	F1
	XLNet$_{\mathrm{BASE}}$ (Yang et al., 2019)	85.6	85.1	93.4	-	-	78.2	81.0
	RoBERTa$_{\mathrm{BASE}}$ (Liu et al., 2019)	84.7	-	92.7	-	90.6	-	79.7
	MPNet$_{\mathrm{BASE}}$ (Song et al., 2020)	86.2	-	**94.0**	85.0	91.4	80.5	83.3
	− relative position bias	85.6	-	93.6	84.0	90.3	79.5	82.2
	UNILMv2$_{\mathrm{BASE}}$ (Bao et al., 2020)	86.1	86.1	93.2	85.6	92.0	80.9	83.6
	− relative position bias	85.6	85.5	93.0	85.0	91.5	78.9	81.8
#1	ERNIE-Gram$_{\mathrm{BASE}}$	**87.1**	**87.1**	93.2	**86.2**	**92.3**	**82.1**	**84.8**
#2	#1− relative position bias	86.5	86.4	93.2	85.2	91.7	80.8	84.0
#3	#2− comprehensive n-gram prediction	86.2	86.2	92.7	85.0	91.5	80.4	83.4
#4	#2− enhanced n-gram relation modeling	85.7	85.8	93.5	84.7	91.3	79.7	82.7
#5	#4− comprehensive n-gram prediction	85.6	85.7	92.9	84.5	91.2	79.5	82.4

Table 6: Comparisons between comprehensive n-gram prediction and enhanced n-gram interaction methods. All the listed models are pre-trained following the same settings of BERT$_{\mathrm{BASE}}$ (Devlin et al., 2019).

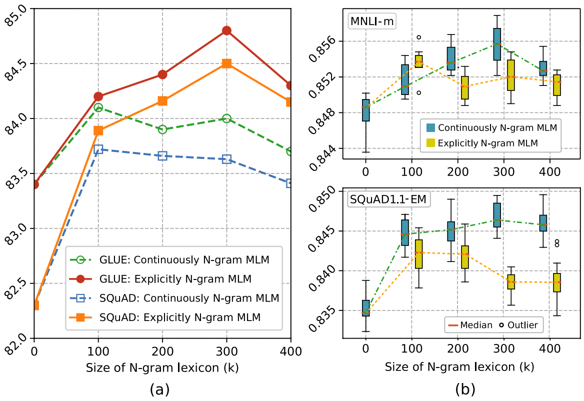


Figure 5: Quantitative study on the size of extracted n-gram lexicon. (a) Results on GLUE and SQuAD benchmarks. Note that GLUE is presented by GLUE average scores, SQuAD is presented by the average scores of SQuADv1.1 and SQuAD v2.0. (b) Performance distribution box plot on MNLI and SQuAD1.1 datasets.

gram MLM with lexicon size being 300K achieves the best results, while the performances significantly decline when the size of lexicon increasing to 400K because more low-frequent n-grams are learning unnecessarily. See Appendix C for detailed results of different lexicon choices on GLUE and SQuAD.

Effect of Comprehensive N-gram Prediction and Enhanced N-gram Relation Modeling. As shown in Table 6, we compare several ERNIE-Gram variants with previous strong baselines under the BERT$_{\mathrm{BASE}}$ setting. We first ablate relative position bias (#2) to compare with XLNet and RoBERTa. After removing comprehensive n-gram prediction (#3), ERNIE-Gram degenerates to a variant with explicitly n-gram MLM and n-gram interaction and its performance drops slightly by 0.3-0.6. When removing enhanced n-gram interaction (#4), ERNIE-Gram degenerates to a variant with comprehensive n-gram MLM and the performance drops by 0.4-1.3. These results demonstrate the advantage of comprehensive n-gram prediction and enhanced n-gram interaction methods for efficiently n-gram semantic injecting in pre-training. The detailed results of ablation study are supplemented in Appendix C.

5 Conclusion

In this paper, we present ERNIE-Gram, an explicitly n-gram masking and predicting method to eliminate the limitations of previous continuous masking strategies and incorporate coarse-grained linguistic information into pre-training sufficiently. ERNIE-Gram conducts comprehensive n-gram prediction and interaction to further enhance the learning of semantic n-grams for pre-training. Experimental results on 19 NLU tasks demonstrate that ERNIE-Gram outperforms XLNet and RoBERTa by a large margin, and achieves state-of-the-art results on various benchmarks. Future work includes constructing more comprehensive n-gram lexicon ($n > 3$), pre-training ERNIE-Gram with large-size model and applying ERNIE-Gram on more downstream NLU tasks.

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A Hyperparameters for Pre-Training

As shown in Table 7, we list the detailed hyperparameters used for pre-training ERNIE-Gram on base and large scaled English text corpora and Chinese text corpora. We follow the same hyperparameters of BERT$_{\text{BASE}}$ (Devlin et al., 2019) to pre-train ERNIE-Gram on the base-scale English text corpora. ERNIE-Gram is still under pre-training with large-scale text English corpora.

Hyperparameters	Base-scale	Large-scale	Chinese
Layers	12		
Hidden size	768		
Attention heads	12		
Training steps	1M	500K	3M
Batch size	256	5112	256
Learning rate	1e-4	4e-4	1e-4
Warmup steps	10,000	24,000	4,000
Adam β	(0.9, 0.99)	(0.9, 0.98)	(0.9, 0.99)
Adam ϵ	1e-6		
Learning rate schedule	Linear		
Weight decay	0.01		
Dropout	0.1		
GPU (Nvidia V100)	16	64	32

Table 7: Hyperparameters used for pre-training on different text corpora.

B Hyperparameters for Fine-Tuning

The hyper-parameters for each tasks are searched on the development sets according to the average score of ten runs with different random seeds.

B.1 GLUE benchmark

The fine-tuning hyper-parameters for GLUE benchmark (Wang et al., 2019) are presented in Table 8.

Hyperparameters	GLUE
Batch size	{16, 32}
Learning rate	{5e-5, 1e-4, 1.5e-4}
Epochs	3 for MNLI and {10, 15} for others
LR schedule	Linear
Layerwise LR decay	0.8
Warmup proportion	0.1
Weight decay	0.0

Table 8: Hyperparameters used for fine-tuning on the GLUE benchmark.

B.2 SQuAD benchmark and RACE dataset

The fine-tuning hyper-parameters for SQuAD (Rajpurkar et al., 2016;Rajpurkar et al., 2018) and RACE (Lai et al., 2017) are presented in Table 9.

Hyperparameters	IMDb	AG'news
Batch size	32	
Learning rate	{5e-5, 1e-4, 1.5e-4}	
Epochs	3	
LR schedule	Linear	
Layerwise LR decay	0.8	
Warmup proportion	0.1	
Weight decay	0.0	

Table 10: Hyperparameters used for fine-tuning on IMDb and AG'news.

Hyperparameters	SQuAD	RACE
Batch size	48	32
Learning rate	{1e-4, 1.5e-4, 2e-4}	{8e-5, 1e-4}
Epochs	{2, 4}	{4, 5}
LR schedule	Linear	Linear
Layerwise LR decay	0.8	0.8
Warmup proportion	0.1	0.1
Weight decay	0.0	0.0

Table 9: Hyperparameters used for fine-tuning on the SQuAD benchmark and RACE dataset.

B.3 Text Classification tasks

Table 10 lists the fine-tuning hyper-parameters for IMDb (Maas et al., 2011) and AG'news (Zhang et al., 2015) datasets. To process texts with a length larger than 512, we follow Sun et al., 2019a to select the first 128 and the last 382 tokens to perform fine-tuning.

B.4 Chinese NLU tasks

The fine-tuning hyper-parameters for Chinese NLU task including XNLI (Conneau et al., 2018), LCQMC (Liu et al., 2018), DRCD (Shao et al., 2018), DuReader (He et al., 2017), CMRC2018 and MSRA-NER (Levow, 2006) are presented in Table 11.

Tasks	Batch size	Learning rate	Epoch	Dropout
XNLI	256	1.5e-4	3	0.1
LCQMC	32	4e-5	2	0.1
CMRC2018	64	1.5e-4	5	0.2
DuReader	64	1.5e-4	5	0.1
DRCD	5	1.5e-4	3	0.1
MSRA-NER	16	1.5e-4	10	0.1

Table 11: Hyperparameters used for fine-tuning on Chinese NLU tasks. Note that all tasks use the layerwise lr decay with decay rate 0.8.

C Detailed Results for Ablation Studies

We present the detailed results on GLUE benchmark for ablation studies in this section. The results on different MLM objectives and sizes of n-gram

Models	**Size of**	**MNLI**	**QNLI**	**QQP**	**SST-2**	**CoLA**	**MRPC**	**RTE**	**STS-B**	**GLUE**	**SQuAD1.1**		**SQuAD2.0**	
	Lexicon	Acc	Acc	Acc	Acc	MCC	Acc	Acc	PCC	**Avg**	EM	F1	EM	F1
$\text{BERT}_{\text{Reimplement}}$	0k	84.9	91.8	91.3	92.9	58.8	88.1	69.7	88.6	83.4	83.4	90.2	76.4	79.2
Contiguously N-gram MLM	100K	85.4	92.3	91.3	92.9	60.4	88.7	72.6	89.6	84.1	84.2	90.8	78.4	81.5
	200K	85.3	92.0	91.5	92.7	59.3	89.0	71.5	89.5	83.9	84.2	90.9	78.3	81.3
	300K	85.1	92.1	91.3	92.8	59.3	88.6	73.3	89.5	84.0	83.9	90.7	78.5	81.4
	400K	85.0	92.0	91.3	93.1	58.3	89.2	71.8	89.1	83.7	83.9	90.7	78.0	81.1
Explicitly N-gram MLM	100K	85.3	92.2	91.4	92.9	62.3	88.6	72.5	88.0	84.2	84.2	90.9	78.6	81.4
	200K	85.4	92.3	91.3	92.8	62.1	88.4	74.5	88.6	84.4	84.5	**91.3**	78.9	81.9
	300K	85.7	92.3	91.3	92.9	62.6	88.7	75.8	89.4	**84.8**	**84.7**	91.2	**79.5**	**82.6**
	400K	84.3	92.2	91.4	92.9	61.3	88.5	73.2	89.3	84.3	84.6	**91.3**	79.0	81.7

Table 12: Results on the development set of the GLUE and SQuAD benchmarks with different MLM objectives and diverse sizes of n-gram lexicon.

#	**Models**	**MNLI**		**QNLI**	**QQP**	**SST-2**	**CoLA**	**MRPC**	**RTE**	**STS-B**	**GLUE**
		m	mm	Acc	Acc	Acc	MCC	Acc	Acc	PCC	**Avg**
#1	$\text{ERNIE-Gram}_{\text{BASE}}$	87.1	87.1	92.8	91.8	93.2	68.5	90.3	79.4	90.4	**86.7**
#2	#1− relative position bias	86.5	86.4	92.5	91.6	93.2	68.1	90.3	79.4	90.6	86.5
#3	#2− comprehensive n-gram prediction	86.2	86.2	92.4	91.7	92.7	65.5	90.0	78.7	90.5	86.0
#4	#2− enhanced n-gram relation modeling	85.7	85.8	92.6	91.2	93.5	64.8	88.9	76.9	90.0	85.5
#5	#4− comprehensive n-gram prediction	85.6	85.7	92.3	91.3	92.9	62.6	88.7	75.8	89.4	84.8

Table 13: Comparisons between several ERNIE-Gram variants on GLUE benchmark. All the listed models are pre-trained following the same settings of $\text{BERT}_{\text{BASE}}$ (Devlin et al., 2019).

lexicon are presented in Table 12. The detailed results on ERNIE-Gram variants to verify the effectiveness of comprehensive n-gram prediction and enhanced n-gram relation modeling mechanisms are presented in Table 13.