

Geo-Encoder: A Chunk-Argument Bi-Encoder Framework for Chinese Geographic Re-Ranking

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Abstract

Chinese geographic re-ranking task aims to find the most relevant addresses among retrieved candidates, which is crucial for location-related services such as navigation maps. Unlike the general sentences, geographic contexts are closely intertwined with geographical concepts, from general spans (e.g., province) to specific spans (e.g., road). Given this feature, we propose an innovative framework, namely *Geo-Encoder*, to more effectively integrate Chinese geographical semantics into re-ranking pipelines. Our methodology begins by employing off-the-shelf tools to associate text with geographical spans, treating them as chunking units. Then, we present a multi-task learning module to simultaneously acquire an effective attention matrix that determines chunk contributions to extra semantic representations. Furthermore, we put forth an asynchronous update mechanism for the proposed addition task, aiming to guide the model capable of effectively focusing on specific chunks. Experiments on two distinct Chinese geographic re-ranking datasets, show that the *Geo-Encoder* achieves significant improvements when compared to state-of-the-art baselines. Notably, it leads to a substantial improvement in the Hit@1 score of MGEO-BERT, increasing it by 6.22% from 62.76 to 68.98 on the GeoTES dataset.

1 Introduction

Chinese geographic re-ranking (CGR) is a sub-task of semantic matching, aiming to identify the most relevant geographic context towards given queries and retrieved candidates (Zhao et al., 2019; MacAvaney et al., 2020; Yates et al., 2021). It is a crucial task that serves many downstream applications such as navigation maps (e.g., Gaode Maps), autonomous driving (e.g., Tesla), E-commerce system (e.g., Taobao), etc. (Jia et al., 2017; Avvenuti et al.,

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Figure 1: Overview of the Chinese Geographic re-ranking task. The process begins with the user query being subjected to word chunking, segmenting it into meaningful units. Lastly, *Geo-Encoder* is employed to enhance semantic representation and re-ranking.

2018). Unlike general query expressions, Chinese geographic sentences exhibit a distinct attribute in their linear-chain structural semantics (Li et al., 2019). This peculiarity arises from the fact that Chinese addresses often comprise distinct meaningful address segments, termed as geographic chunks in linguistic terms (Abney, 1991). These chunks adhere to a specific format, organizing from the general (e.g., province) to the more specific (e.g., road). For example, as is shown in Figure 1, given a Chinese address “采荷路2号高级中学北门 (*North Gate of Caihe Road No.2 Senior High School*)”, we can deconstruct it into several such chunks: “采荷路 (*Caihe Road*)”, “2号 (*No.2*)”, “高级中学 (*Senior High School*)”, “北门 (*North Gate*)”.

Conventional approaches (Reimers and Gurevych, 2019; Humeau et al., 2019; Khattab and Zaharia, 2020) addressing the CGR task often directly employ pre-trained language models (PLMs) to encode given geographic texts into embeddings, which are subsequently subjected

to re-ranking through similarity calculation techniques like cosine or euclidean distance measures. Recent works (Yuan et al., 2020; Huang et al., 2022; Ding et al., 2023) in this field extend beyond mere geographic context utilization and encompass an expansive range of data sources, including point-of-interest information, multi-modal data, and user behavioral attributes (Liu et al., 2021; Hofmann et al., 2022; Huang et al., 2022) with a larger neural model. The outcome of this integration is characterized by notable enhancements, achieved through the fusion of external geographic knowledge. Furthermore, cutting-edge domain-adaptation frameworks have been introduced to facilitate effective fusion of multi-domain data, such as PALM (Zhao et al., 2019), STDGAT (Yuan et al., 2020), etc.

However, despite the effectiveness of existing attempts in leveraging geographic knowledge, these methods failed to fully harness the intrinsic potential of the geographic context itself. Therefore, in this paper, we aim to shift our focus towards the geographic context by exploiting its distinctive linear-chain attributes. To achieve this, we employ off-the-shelf tools (e.g. MGEO tagging¹ and part-of-speech (POS)² for the approximate annotation of each geographic text with pertinent geographic chunks. For example, as illustrated in Figure 1, we annotate the text “采荷路 (Caihe Road)” with the label *Road*, “2号 (No.2)” with *Num*, etc.

Firstly, building upon this foundation, we introduce an additional task that revolves learning the similarity between different components of these annotated chunks. This involves the formulation of an attention matrix, which governs the contributions of these chunks to the semantic representations. Our motivation is that general chunks tend to be less diverse across queries and candidates, and specific chunks possess a higher degree of distinctiveness. **Secondly**, we put forth a novel asynchronous update speed mechanism for the attention matrix. This mechanism is designed to empower the model to effectively focus its attention on the more specific chunks, thereby enhancing its discernment capabilities. **Lastly**, we advocate for the integration of the pure bi-encoder approach during the inference period. This strategy ensures a har-

monious balance between performance and computational efficiency, safeguarding the efficacy of the model in both academic and industrial scenarios.

In summary, our key contributions are as follows: 1) We introduce a multi-task learning framework, denoted as *Geo-Encoder*, which serves as a pioneering approach to integrate component similarity; 2) We present an asynchronous update mechanism, to distinguish specific chunks effectively; 3) Except evaluation on benchmark dataset, we collect and publish a nationwide geographic dataset in China, named GeoIND. Experimental results on two distinct Chinese geographic re-ranking datasets demonstrate the superiority of our *Geo-Encoder* over competitive methods. Our code and datasets are available at: https://github.com/yongcaoplus/CGR_damo.

2 Related Work

Semantic Matching and Re-Ranking. Semantic matching is a widely-concerned task in natural language processing, including retrieval and re-ranking process (Zhao et al., 2019; Yates et al., 2021). Different from retrieval task, re-ranking generally deal with smaller candidates. Within this domain, researchers employ bi-encoders to encode given queries and candidates separately by using the shared parameters, such as ESIM (Chen et al., 2017), SBERT (Reimers and Gurevych, 2019), ColBERT (Khattab and Zaharia, 2020), etc. And after the emergence of pre-trained models, such as RoBERTa (Liu et al., 2019), ERNIE (Sun et al., 2021), cross-encoders were proposed to jointly encode text and promote the information interaction (Humeau et al., 2019; Nie et al., 2020; Ye et al., 2022). Besides, to better represent sentences, external knowledge and late interactions were widely explored. For example, Xia et al. (2021) utilized a word similarity matrix to assign term weights for given tokens, and Peng et al. (2022) introduced predicate-argument spans to enhance representation. Notably, the bi-encoder is industry-preferred for its efficiency thus we adopted it in our paper.

Chinese Geographic Text Representation. Most existing approaches focused on encoding geographic text by external knowledge in two aspects: (1) position data, such as PALM (Zhao et al., 2019), encoding positional relationship of query and candidates, STDGAT (Yuan et al., 2020), considering Spatio-temporal features, etc.; (2) geographic knowledge, such as GeoL (Huang

¹https://modelscope.cn/models/damo/mgeo_geographic_elements_tagging_chinese_base/summary.

²POS tagging is based on jieba: <https://github.com/fxsjy/jieba>.

et al., 2022), using knowledge related to user behaviors, and MGeo (Ding et al., 2023), proposing using multi-modal dataset. However, the geographic text encoding method among the above approaches is not well-explored. Besides, parsing Chinese geographic text into chunks is also a key technical issue (Li et al., 2019). Generally, address parsing is quite similar to Chinese word segmentation. Existing attempts to Chinese word segmentation includes CRF models (Zhao et al., 2006), latent-variable variants (Sun et al., 2009), neural transition-based segmentation method (Zhang et al., 2016), and chart-based models (Stern et al., 2017; Kitaev and Klein, 2018), etc. However, while these models benefit from external geographic knowledge, exploring text representation optimization beyond direct PTMs encoding is still crucial.

3 Our Approach

3.1 Task Definition and Overview

In Chinese Geographic Re-ranking (CGR) task setting, the available dataset $\{X\}$ is formed as query-candidate pairs. Let Q denotes queries and C as retrieved candidates, where C is the corresponding candidates list of each query from Q . Both Q and C are composed of l separated tokens, where $\{X\} = \{X \in (Q, C) | X = x_1, x_2, \dots, x_l\}$. The objective of CGR is to model the highest possibility of C . Thus, the bi-encoder framework, depicted in Figure 3(a), can be formalized as:

$$c = \arg \max_C r_\theta (f_\theta(Q), f_\theta(C)) \quad (1)$$

where f_θ denotes encoding function (we adopt PLMs here), to encode given text into vectors, c ($\in C$) is the model output and r_θ denotes similarity evaluation function, such as dot multiple and cosine similarity, to assign a similarity score for each candidate. Also, the cross-encoder framework, depicted in Figure 3(b) can be formalized as:

$$c = \arg \max_C r_\theta (f_\theta(Q, C)) \quad (2)$$

Most current attempts directly deploy PTMs to encode geographic texts into embeddings (Yuan et al., 2020; Huang et al., 2022; Ding et al., 2023), ignoring the linear-chain structure characteristic of geographic text. To quantify this distinction, we calculate the entropy score of geographic chunking datasets from (Li et al., 2019) as shown in Figure

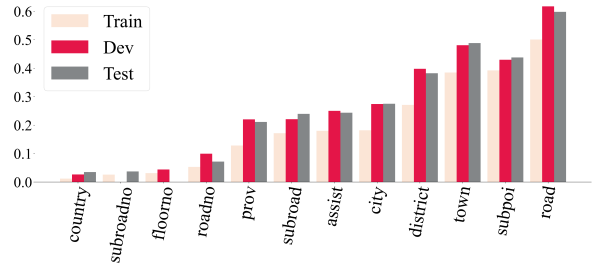


Figure 2: The information entropy of Li et al. (2019), indicate that specific chunks (e.g., road) exhibit greater diversity compared to general ones (e.g., country).

2. Obviously, the specific chunks (e.g. road, town, etc.) hold a higher entropy score among all sets, revealing more diversity than the general chunks (e.g. country, province, etc.). Therefore, it can be further inferred that specific chunk components contribute unequally to the semantic representation of sentences, indicating that specific chunks play a more substantial role than general ones.

In our approach, we strive to enhance the encoding process through a two-step strategy. Firstly, we segment the provided geographic text into chunks and introduce a novel approach to learn both the attention matrix governing chunk contributions and component semantic representation as an additional task. Secondly, we introduce an asynchronous update mechanism for the attention matrix and model parameters. This mechanism is aimed at enabling the model to efficiently acquire the skill of focusing on specific chunks. Finally, we present our training and inference details. The detailed framework of our proposed method, called *Geo-Encoder*, is shown in Figure 3(c).

3.2 Geographic Chunking

Chinese addresses typically consist of multiple meaningful address segments, often referred to as "geographic chunks" (Abney, 1991). These addresses follow a structured pattern, progressing hierarchically from the general (e.g., province) to specific ones (e.g., road) (Li et al., 2019). In contrast to conventional Chinese segmentation methods, geographic chunking demands tools of heightened sensitivity tailored to geographical units. These tools necessitate fine-tuning using dedicated Chinese address corpora. Consequently, we adopt the MGeo tagging tool to facilitate the acquisition of precise geographic annotations for our benchmark datasets (Wu et al., 2022a,b; Ding et al., 2023).

MGeo stands as a pre-trained model with multi-

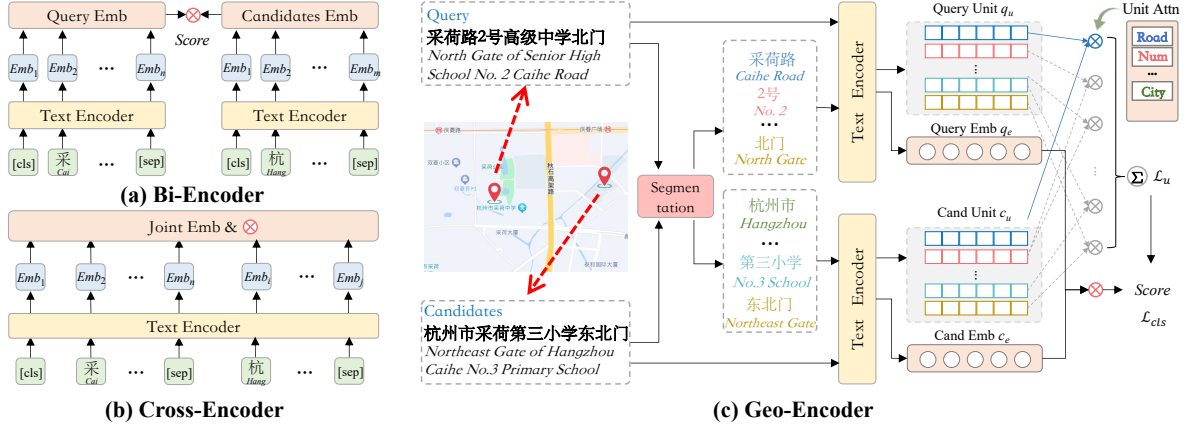


Figure 3: Architecture of re-ranking models and our proposed Geo-Encoder. The left shows the bi-encoder and cross-encoder models, and the right shows our proposed Geo-Encoder, which parsing geographic text into chunking units and jointly encoding with global features and unit attention mechanism. \otimes denotes similarity calculation.

modal datasets, encompassing both geographic context and points of interest. It is designed to cater to various downstream tasks, including geographic entity alignment and address element tagging, among others. In our current framework, however, we exclusively leverage MGEO to provide chunk annotations, without employing it for the purpose of encoding contextual information. Then, dataset $\{X\}$ is extended as $\{X_u\} = \{x \in (Q, C, Q_u, C_u) | X = x_1, x_2, \dots, x_n\}$, where Q_u and C_u denotes query and candidates chunking units. For example, given a Chinese address “南京市新城科技园3栋5单元(Unit #5, Building #3, Sci-Tech Park, Nanjing City.)”, we can parse them by MGEO into: “南京市(Nanjing City)” – city, “新城科技园(Sci-Tech Park)” – devzone, “3栋(Building #3)” – houseno, “5单元(Unit #5)” – cellno.

3.3 Chunking Contribution Learning

Utilizing the chunked dataset denoted as $\{X_u\}$, we proceed to employ a pre-trained language model for the encoding process. This yields the representations of $[CLS]$ embedding e_{cls}^q and token embedding $e_{1:l}^q$ from geographic text:

$$e_{cls}^q, e_{1:l}^q = Encoder(q), q \in Q \quad (3)$$

where $Encoder$ denotes PTMs. And correspondingly we can get candidates features e_{cls}^c and $e_{1:l}^c$. Given chunking annotations, we initialize a zeros query component embeddings $\{U^Q | u_i^q \in U^Q\}$, $i = \{1, 2, \dots, M\}$ and we can further update query component embeddings u_i^q by:

$$u_i^q = mean(\Gamma(e_{1:l}^q, I_i^q)) \quad (4)$$

where $\Gamma(\cdot)$ is the Index function to obtain component token embeddings, M is the total amount of chunk categories, and I_i^q is the index number acquired by the tokenizer of the $Encoder$ from the chunk’s location to the corresponding query. Similarly, component embeddings $\{U^C | u_i^c \in U^C\}$ can also be obtained. We can also get candidates’ component embeddings u_i^c similar with Eq. 4.

To incorporate token-level embeddings, the CoBERT model (Khattab and Zaharia, 2020) introduced a multi-attention mechanism, which facilitates subsequent interactions between queries and candidates. This technique has demonstrated improved efficacy in re-ranking tasks. Nonetheless, it is essential to acknowledge that the CoBERT method entails significant additional computational resources. In light of this, our work introduces an innovative multi-task learning module that incorporates only geographic chunking component embeddings and utilizes an attention matrix to fuse results. This approach is designed to address the need for efficient resource utilization while maintaining or potentially improving performance.

Specifically, we define an attention matrix that can be learned along the training process, denoted as W_U . Then, we can get the predictions from component embeddings:

$$Score_u = (U^Q * W^U) * (U^C * W^U) \quad (5)$$

We use dot multiplication to obtain the similarity scores of given queries and candidates. Thus, for components embeddings, we can obtain the component similarity loss \mathcal{L}_u as:

$$\mathcal{L}_u = \Phi(\text{Score}_u, Y) \quad (6)$$

where Y represents the ground truth ranking results, and $\Phi(\cdot)$ signifies the cross-entropy loss function.

As for the primary task, we use $[CLS]$ representation as sentence encoded features, and we can obtain the semantic similarity loss \mathcal{L}_{cls} as:

$$\mathcal{L}_{cls} = \Phi(E_{cls}^Q * E_{cls}^C, Y) \quad (7)$$

where $e_{cls}^q \in E_{cls}^Q$ and $e_{cls}^c \in E_{cls}^C$.

Discussion. Due to the components of each geographic text being quite different, introducing feature concatenation strategy in CGR task is not reasonable. Therefore, we proposed to use an universal component embeddings for queries U^Q and candidates U^C , and initialize them as zero matrices. It follows that empty components would yield no contributions to the final representations. Similarly, components that do not align appropriately between the queries and candidates would also have no impact.

3.4 Asynchronous Update Mechanism

For multi-task learning, a common concern is the disparate challenges faced by models when learning multiple tasks simultaneously, often leading to variations in convergence rates (Lu et al., 2017; He et al., 2017). In our pursuit to tackle this quandary within our designated task, we deviate from established methodologies seen in prior literature (Isonuma et al., 2017; Hashimoto et al., 2017; Nishino et al., 2019; Pfeiffer et al., 2020). Instead, we propose an innovative approach involving the integration of an asynchronous update mechanism, which allocates enhanced focus on training steps pertaining to distinct tasks. To formalize our proposition, the update of parameter $w_u (w_u \in W_U)$ is as:

$$w'_u = w_u + \lambda \cdot \nabla w_u \cdot \gamma \quad (8)$$

where γ is a hyper-parameter to adjust training speed, which can set by grid search or empirically.

Discussion. Our insights is that the fast distinction of specific geographic chunks should conceivably be more amenable and expedited for the model’s learning process. Consequently, the matrix W_U could feasibly adapt to more substantial increments in learning steps compared to those attributed to language model parameters.

3.5 Training and Inference

During the training process of CGR, we deploy our proposed framework *Geo-Encoder* of Figure 3(c). The model can be optimized by jointly minimizing the semantic similarity loss and component similarity loss:

$$\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_u \quad (9)$$

During the inference phase, a notable concern arises from the time-intensive nature of indexing and calculating component embeddings, particularly when extrapolated to scenarios involving an extensive pool of candidates. To circumvent this challenge, we directly adopt a bi-encoder framework for conducting inference, as visually depicted in Figure 3(a).

Discussion. Our rationale for introducing components stems from a deliberate consideration of the trade-off between training and inference aspects. The underlying objective is to facilitate the model in exhibiting a heightened sensitivity towards specific chunks as opposed to general ones. This endeavor has yielded demonstrably effective outcomes in our experimental evaluations. Conversely, during the inference phase, we eliminate the necessity for component predictions, thereby leading to a marked improvement in computational efficiency. This assertion will be substantiated in the subsequent section.

4 Experiment

4.1 Datasets

To comprehensively validate the efficacy of our Geo-Encoder, we prepared two representative Chinese geographical datasets: (i) **GeoTES**: a widely-recognized, large-scale benchmark dataset, and (ii) **GeoIND**: our collected moderately-sized, real-world industry dataset. The statistical details concerning the two datasets are presented in Table 1.

Geographic Textual Similarity Benchmark

(GeoTES): This large-scale dataset comprises queries meticulously crafted by human annotators and was amassed within the location of Hangzhou, China.³ The dataset’s meticulous annotation was executed by a panel of 20 participants and four domain experts. Encompassing a total of 90,000

³The dataset can be downloaded here: <https://modelscope.cn/datasets/damo/GeoGLUE/summary>.

queries, each complemented by 20/40 retrieved candidates, this dataset extends its scope beyond geographical text, encapsulating supplementary point of interests (POIs) data. Please refer to Appendix for more details.

Industry Geographic dataset (GeoIND): For a broader validation, we re-organize and format an additional real-world dataset named GeoIndustry, sourced from a geographic search engine. This dataset underwent rigorous cleaning and filtration procedures, effectively eliminating noise and erroneous queries. In contrast to GeoTES, this dataset exhibits an intermediary scale, yet it boasts a substantial geographical coverage. We will make it publicly available upon the publication of our work.

4.2 Baselines

To assess the effectiveness of our Geo-Encoder, we undertake a comprehensive comparative analysis via representative bi-encoder methodologies. It’s pertinent to mention that our assessment confines itself exclusively to geographic text data, with the exclusion of Points of Interest (POIs) or other modal data. Our selected baselines include:

- **Word2Vec** (Mikolov et al., 2013). A traditional method captured semantic relationships between words and encoded words as dense vector embeddings.⁴
- **Glove** (Pennington et al. 2014). It encapsulated both global and local semantic information and served for contextual understanding.
- **SBERT** (Reimers and Gurevych, 2019). A popular bi-encoder model that can effectively and efficiently serve for re-ranking task.⁵
- **Argument-Encoder** (Peng et al., 2022). It first proposed that concatenate predicate-argument embedding as extra representations can enhance re-ranking task.⁶
- **MGEO** (Ding et al., 2023). By applying geographic POIs information to fuse external knowledge into encoder, this method achieves state-of-the-art results in current task.⁷

⁴Reproduced by text2vec package(Xu, 2023): <https://github.com/shibing624/text2vec>.

⁵<https://github.com/UKPLab/sentence-transformers>.

⁶We reproduce this method by replacing the predicate-argument with specific geographic-argument.

⁷We compare three backbone models with MGEO in text-only modal data, including BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and ERNIE 3.0 (Sun et al., 2021).

Benchmark	Sets	Query	Tokens	ASL	Cands
GeoTES	Train	50,000	3,599	18.8	20
	Dev	20,000	3,322	17.2	40
	Test	20,000	3,351	17.1	40
GeoIND	Train	7,359	3,768	15.1	20
	Dev	2,453	3,376	15.1	20
	Test	2,469	2,900	15.0	20

Table 1: The statistics of two datasets. *Tokens* denotes vocabularies counts, *ASL* denotes the average sentence length, and *Cands* represents candidates numbers.

Importantly, in real-world scenarios, accounting for computational efficiency is imperative. Therefore, in light of this consideration, we opt for the bi-encoder approach coupled with the current backbone models, rather than adopting the cross-encoder methodology or large language models.

4.3 Experimental Setting

Evaluation Metrics. Following previous re-ranking tasks (Qu et al., 2021; Ding et al., 2023), we use Hit@K(K=1,3), NDCG@1 (Järvelin and Kekäläinen, 2002) and MRR@3 to evaluate the performance across all models. Specifically, Hit@K quantifies the proportion of retrieved candidates that include at least one correct item within the top K ranks. NDCG@1 is a graded relevance measure that takes into account the positions of relevant items in the ranked list. MRR@3 calculates the average of the reciprocal ranks of the top-3 correct answers in the ranked list.

Hyper-parameters. For finetuning, we set the learning rate is set as 1e-5 for RoBERTa and 5e-5 for BERT and ERNIE. We finetune models for 50 epochs with early stopping after 3 epochs of no improvement in Hit@1 on the validation set. We conduct our experiment on a single A100 GPU and optimize all the models with Adam optimizer, where the batch size is set to 32. And followed by Ding et al. (2023), we decrease the embedding dimension from 768 to 256.

4.4 Main Results

We have conducted a rigorous comparison between our method with the aforementioned baselines and the results are presented in Table 2.

Firstly, it is evident that our proposed approach achieves a remarkable state-of-the-art performance across all evaluated metrics, surpassing the performance exhibited by all alternative methods. This observation provides compelling evidence that our

Model	GeoTES				GeoIND			
	Hit@1	Hit@3	NDCG@1	MRR@3	Hit@1	Hit@3	NDCG@1	MRR@3
Word2vec (Mikolov et al., 2013)	19.26	30.60	28.79	24.15	47.79	71.69	66.15	58.27
Glove (Pennington et al. 2014)	48.02	67.33	63.32	59.35	52.38	74.87	71.95	69.35
SBERT (Reimers and Gurevych, 2019)	24.22	51.22	46.65	35.80	42.20	71.24	64.56	54.92
Argument-Encoder (Peng et al., 2022)	56.54	80.01	73.47	67.08	59.58	85.54	78.61	71.19
MGEO-BERT (Ding et al., 2023)	62.76	80.89	75.95	70.87	64.12	88.66	81.35	75.04
<i>Geo-Encoder</i>	68.98	85.82	81.11	76.56	66.71	89.35	82.78	76.99
MGEO-ERNIE (Ding et al., 2023)	67.50	84.54	79.60	75.15	63.95	87.89	81.06	74.60
<i>Geo-Encoder</i>	68.66	85.64	80.75	76.30	65.33	89.06	82.10	75.98
MGEO-RoBERTa (Ding et al., 2023)	68.74	85.16	80.63	76.15	63.63	88.70	81.62	74.81
<i>Geo-Encoder</i>	70.39	86.69	81.97	77.72	67.27	90.28	83.61	77.56

Table 2: Main results on GeoTES and GeoIND, where bold values indicate the best performance within each column. Our proposed method consistently outperforms all three baselines across all metrics on both datasets.

Geo-Encoder yields significant enhancements over multiple baseline models. Particularly, our method improves the Hit@1 score of BERT by 6.62% from 62.76 to 68.98 on GeoTES dataset, and by 2.59% from 64.12 to 66.71 on GeoIND dataset.

Secondly, comparing three different backbone pre-trained models, RoBERTa performs emerges as the superior candidate, surpassing both BERT and ERNIE. This advantage can be attributed to RoBERTa’s augmented network depth and its exposure to a comprehensive training corpus, endowing it with a heightened capacity for contextual comprehension and modeling than other models.

Thirdly, a notable trend is that the GeoTES dataset is marginally more amenable to learning compared to the GeoIND dataset, a phenomenon primarily attributed to its significantly larger scale, which is 6.76 times greater. This distinction is corroborated by the highest attained Hit@1 score of 70.39 on the GeoTES dataset, as opposed to the score of 67.27 observed on the GeoIND dataset.

Furthermore, we can also conclude that conventional encoding methodologies such as word2vec, GloVe, and SBERT exhibit subpar performance in CGR tasks. And it is pertinent to mention that in the context of the CGR task, cosine similarity tends to exhibit suboptimal performance compared to dot multiplication. This is evident from the fact that SBERT yields lower performance scores across both datasets. Similarly, the argument-enhancement techniques and the MGEO bi-encoder manifest a consistently underwhelming performance across both datasets.

5 Analysis and Discussion

In this section, we first conduct a comprehensive analysis of our proposed modules, and then discuss the advantages of using Geo chunking for CGR task. Lastly, a detailed exploration of hyperparameter setting and the learned chunking attention metric is presented for a deeper understanding.

5.1 Fix Contribution vs. Learning Weight

In accordance with human experiential knowledge, the common practice involves the gradual differentiation of an address by sequentially hypothesizing the constitutive chunking elements, transitioning from general segments to more precise ones. Evidently, the generalized segments found among the pool of candidates tend to exhibit significant similarity, thus warranting a diminished influence on the semantic alignment process towards given queries. On the basis of this underlying hypothesis, we have formulated a comparative experiment intended to investigate the potential benefits arising from the dynamic allocation of chunk contributions in the context of representation learning.

Specifically, we constructed an experimental framework wherein the dynamic interplay of chunk contributions is examined. This is realized by configuring the attention matrices within the *Geo-Encoder* architecture as constant values, effectively precluding gradient updates. We fix the attention weight with the values of 0.1, 0.5, and 1.0 respectively, thereby probing the impact of different attention allocation strategies on the learning process.

As is shown in Table 3, we can find that the imposition of fixed attention matrices contributes to a reduction in the performance of the *Geo-Encoder* across both datasets. Besides, the diverse initializa-

Method	Hit@1	Hit@3	NDCG@1	MRR@3
GeoTES				
baseline	62.76	80.89	75.95	70.87
w Fixed_1.0	68.08	85.35	80.48	75.84
w Fixed_0.5	66.02	83.91	78.97	74.03
w Fixed_0.1	68.19	84.95	80.31	75.70
w POS (<i>Ours</i>)	68.25	85.55	80.65	76.02
w Geo (<i>Ours</i>)	68.98	85.82	81.11	76.56
GeoIND				
baseline	64.12	88.66	81.35	75.04
w Fixed_1.0	65.61	89.59	82.47	76.39
w Fixed_0.5	65.69	89.06	82.28	76.23
w Fixed_0.1	64.20	87.85	81.14	74.77
w POS (<i>Ours</i>)	65.21	89.59	82.24	76.06
w Geo (<i>Ours</i>)	66.71	89.35	82.78	76.99

Table 3: Ablation study on GeoTES and GeoIndust Sets, including exclude automatic attention update mechanism and geographic chunking information.

tion schemes for these attention matrices yield distinct effects among datasets. Within the GeoTES dataset, an initialization ratio of 0.1 yields optimal results, indicating a higher reliance on the sentence-level $[CLS]$ representation. Conversely, the GeoIND dataset attains peak performance when the ratio is set to 1.0, implying a contrasting attention distribution trend. Lastly, we find that even exclude the automatic update of attention matrices, the resultant performance still surpasses that of the baseline models. This outcome underscores the benefits derived from the incorporation of chunking information, substantiating its constructive impact on enhancing the overall model performance.

5.2 Geo Chunking vs. General Chunking

Subsequently, our investigation delves deeper into the influence of geographic chunks (Geo) by conducting a substitution experiment wherein these chunks are replaced with Part-of-Speech (POS) tagging results. To achieve this, we employ the jieba POS tagging tool to restructure the two datasets⁸. It is essential to note that the core distinction between POS and Geo lies in the target of segmentation: while GEO is geared towards geographic ontology, POS is more focused on semantic components.

The results, as depicted in Table 3, yield an interesting observation that employing POS tagging can benefit both datasets, signified by the obvious superior performance of POS when compared to the baseline. This favorable outcome can be at-

⁸To ensure a fair comparison, we manually select relevant POS labels (e.g., quantity, noun, position, etc.), while excluding irrelevant ones (e.g., tone, punctuation, preposition, etc.). Further details can be found in the Appendix.

Method	GeoTES		GeoIND	
	Training (hour)	Inference (ms/case)	Training (hour)	Inference (ms/case)
Word2vec	–	5.9	–	3.5
Augment-Encoder	6.24	32.7	1.52	15.8
MEGO-BERT	4.50	33.8	0.92	18.9
<i>Geo-Encoder</i>	5.94	35.6	1.25	19.5

Table 4: The statistics of training and inference time across different bi-encoder baseline models and our proposed *Geo-Encoder* on GeoTES and GeoIND datasets.

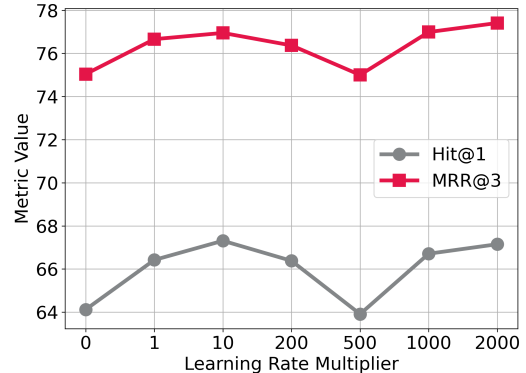


Figure 4: Comparing performance with varying learning rate multiplier ratios on the GeoIND dataset. The learning rate multiplier signifies the ratio of attention matrix learning rate to model parameter learning rate.

tributed to the additional representation and multi-task learning introduced by our approach. Nevertheless, it is noteworthy that despite the advantageous performance of POS, it lags behind Geo in terms of performance. This discrepancy further underscores the pivotal role played by geographic chunks in the context of the CGR task. Irrespective of the approach used for segmentation, our framework consistently exhibits better performance, thereby reinforcing *Geo-Encoder*'s adaptability and efficacy. Therefore, our proposed framework transcends the confines of the Chinese task, and holds relevance and applicability to other languages or tasks characterized by sentence structures that align with linear-chain attributes.

5.3 Parameter Sensitivity and Efficiency

Considering the pivotal impact of the dynamic attention matrix on model performance, we have conducted an additional experiment involving different update speed for model parameters and the attention matrix, which we called asynchronous learning rate updates. The outcomes, as is shown in Figure 4, underline the sub-optimal nature of synchronously updating metrics with model param-

datasets. This discrepancy aligns with the consistent low correlation scores observed between ERNIE and other models, as presented in Table 5.

Moreover, to probe the consistency across diverse learning processes, we compute spearman correlation coefficients (Spearman, 1961) across different datasets. Illustrated in Table 5, all of these correlation coefficients exhibit positive correlations and most of the results are statistically significant, underscoring uniform learning outcomes in component weights. It is worth noting that, except for the ERNIE model on the GeoTES dataset, the majority of models and datasets exhibit robust correlations, which is obviously evidenced by the high correlation scores. This result aligns with the observation that the ERNIE backbone model attains marginal enhancement, as shown in Table 2. Lastly, models trained on the same datasets yield notably high correlation scores among themselves. For instance, the scores between indBERT and indRoBERTa, and similarly between tesBERT and tesRoBERTa, surpass the 0.78 threshold.

6 Conclusion

In this paper, we proposed a novel framework called *Geo-Encoder* for Chinese geographic re-ranking task by deploying multi-task learning module and synchronous update mechanism. The key idea behind *Geo-Encoder* is to encode geographic text using an additional component learning representations from address chunks. This approach allows the *Geo-Encoder* to effectively leverage linear-chain characteristic of geographic contexts, which guides the model to capture subtle distinctions among different candidates. Moreover, we present an attention matrix that enables the model to automatically learn the significance of geographic chunking components within the representation. To address the varying levels of task complexity, we introduced an asynchronous update mechanism for iterative adjusting the weight matrix of these components. This dynamic adjustment facilitates the the focus of model on specific chunks efficiently. Extensive experiments demonstrated that our proposed framework leads to significant improvements over several competitive baselines. Future work could be incorporating our approach in multi-modal and multi-lingual tasks.

7 Limitations

While our work has achieved good performance and shown promising results in enhancing Chinese geographic re-ranking task through incorporation of geographic representations, there are still limitations in our work. Specifically, the Geo-Encoder we have developed exhibits a specificity towards textual data possessing linear-chain or structural characteristics, thereby constraining the method’s applicability primarily to within-domain scenarios. However, we believe that this study is still useful in highlighting the challenges of geographic encoding. Moreover, our approach demonstrates notable effectiveness and efficiency when employed in industrial applications, owing to its minimal augmentation of parameters.

In the future, we plan to explore the feasibility of collecting multi-modal datasets, which can be potential to provide further insights into incorporating geographic understanding with our proposed framework into CGR task.

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A Appendix

A.1 Dataset Details

As previously mentioned, we utilize the MGEO geographic tagging tool¹⁰ to thoroughly annotate the provided geographical text. To elaborate further, we present a demonstrative instance in Table 11. This example highlights the effectiveness and comprehensive nature of the MGEO in annotating geographical information within the text.

A.2 POS Implement

We utilize the Jieba tagging tools, which enable the segmentation of all geographical text into meaningful segments. Following this initial breakdown, a rigorous selection process is undertaken, wherein 28 specific parts-of-speech categories are identified as pertinent and aligned with our Geo tagging system. These categories are chosen based on their close relevance to geographical references, thereby ensuring the precision of the tagging process. A comprehensive list of these valid part-of-speech tags is provided in Table 10.

In this context, it’s important to emphasize that even though manual selection involves a degree of subjectivity, we have maintained consistent tag categories with geographical references to ensure a fair comparison. Additionally, although certain POS tags may not directly pertain to geographic terminology, we have arranged them based on their relative correlations across all POS tags. We have also provided a list of POS tags that are deemed invalid in Table 9, consisting of 24 specific parts-of-speech categories.

Moreover, we compute the fuzzy similarity¹¹ between the results of POS tagging and Geo chunking, as shown statistically in Table 6.

As depicted in Table 6, it becomes evident that the average count of Geo chunking units is less than that of POS. Concurrently, a noteworthy inference can be drawn that the chunking outcomes exhibit resemblance. This is supported by the substantial similarity scores (exceeding 78.00) between the results on both datasets.

A.3 Geo Chunks

We have compiled a comprehensive table (Table 8), that outlines various chunking categories along

¹⁰https://modelscope.cn/models/damo/mgeo_geographic_elements_tagging_chinese_base.

¹¹<https://pypi.org/project/fuzzywuzzy/>

Set	Avg. Geo	Avg. POS	Similarity
GeoTES			
Train	5.11	10.71	80.56 ± 7.39
Dev	4.69	9.47	80.46 ± 7.35
Test	4.66	9.41	80.60 ± 7.41
GeoIND			
Train	4.38	8.59	78.50 ± 6.46
Dev	4.38	8.60	79.71 ± 6.65
Test	4.37	8.57	79.77 ± 6.68

Table 6: Valid POS categories and their respective definitions, comprising a total of 28 categories.

Parameter	GeoTES	GeoIND
<i>Learning rate(BERT)</i>	5e ⁻⁵	5e ⁻⁵
<i>Learning rate(RoBERTa)</i>	1e ⁻⁵	1e ⁻⁵
<i>Learning rate(ERNIE)</i>	5e ⁻⁵	5e ⁻⁵
<i>Batch size</i>	32	32
<i>Test Batch size</i>	16	16
<i>Early Stop</i>	3	3
<i>Embed_dim</i>	256	256
<i>Optimizer</i>	AdamW	AdamW
<i>Attn_init</i>	1.0	1.0
<i>Weight_decay</i>	0.02	0.02

Table 7: The hyper-parameters of the best results on GeoTES and GeoIND dataset.

with their corresponding definitions of Geo chunks. Drawing from our accumulated expertise, we have classified all chunk categories into two distinct groupings: "general" and "specific."

This categorization is guided by a systematic process that sorts these categories based on their relative degrees of correlation. To elaborate on this process, we strategically designate the first 50% of the selection as general chunks, while the subsequent 50% are categorized as specific chunks. By employing this division strategy, we achieve a balanced representation of both general and specific chunk types.

A.4 Hyper-parameter Setting

In an effort to support the reproducibility of the *Geo-Encoder* and its demonstrated reasoning performance, we are providing a compilation of the optimal hyperparameters that yielded the best outcomes on two benchmark datasets, as illustrated in Table 7.

In the process of establishing the baseline, it’s important to note that all scores presented in Table 2 have undergone training and validation on a consistent hardware platform. Additionally, we are committed to making our baseline code publicly

Chunks	Definition
General	
PA	Country
PB	Province
PC	City
PD	District
PE	Township
PF	Street
PG	Village
PH	Administrative Term / Business District
PS	Other Administrative Term
UA	Door Address: Road xx, No.xx / Lane xx
UB	Door Address: Building xx / Area xx
UC	Door Address: Building No. xx
UD	Door Address: Additional Description
Specific	
BS	Bus Station
BL	Bus and Subway Route
RD	Road, Highway, Furuin Street, Tunnel, Bridge, Overpass
Entity	General Name for Point of Interest (POI)
Brand	Well-known Brand
CategorySuffix	Category Suffix Word
Ent	Point of Interest (POI)
Br	Brand
No.	Number
UE	Door Address: East Entrance, South Gate
SA	Direction Modifier
PH	Administrative Term / Business District
Ye	Semantic Connector
Des	Descriptor
ZZ	Unknown

Table 8: Translation of Chunking Terms.

available for reference, which will coincide with the release of our paper.

Invalid POS tag	Definition
e	Interjection
i	Idiom
d	Adverb
l	Idiomatic Expression
p	Preposition
u	Particle
y	Modal Particle
g	Morpheme
x	Non-Morpheme Character
vg	Verbal Morpheme
vn	Nominal Verb
zg	State Morpheme
r	Pronoun
dg	Adverbial Morpheme
tg	Tense Morpheme
o	Onomatopoeia
uj	Particle
ud	Particle
nr	Personal Name
rg	Modal Particle
ul	Tense Particle
s	Locative Noun
nrt	Personal Name
nrfg	Personal Name

Table 9: Invalid POS categories and their respective definitions, consisting of a total of 24 categories.

Valid POS tag	Definition
nz	Other Proper Noun
a	Adjective
m	Numeral
q	Measure Word
t	Time Word
mg	Measure Word for Quantity
ns	Place Name
ng	Noun as Morpheme
ag	Adjective as Morpheme
f	Locative
z	Status Word
nt	Organization Name
eng	English Word
an	Noun
mq	Measure Word for Quantity
ad	Adverb as Adjective
b	Differentiation Word
j	Abbreviation
n	Noun
c	Conjunction
uv	Auxiliary Word
k	Following Part
h	Preceding Part
v	Verb
uz	Status Word
ug	Tense Word
df	Differentiation Word
yg	Modal Particle

Table 10: Valid POS categories and their respective definitions, comprising a total of 28 categories.

Field	Content
Query	浙江省杭州市人民检察北东院侧广播电视台东门南 South of the East Gate of People’s Procuratorate North East Radio and Television Station, Hangzhou City, Zhejiang Province.
Query_Geo_Chunks	浙江省-prov / 杭州市-city / 人民检察-poi/ 东院-subpoi / 侧-assist / 广播电视台-subpoi / 东门-subpoi / 南-assist Zhejiang Province / Hangzhou City / People’s Procuratorate / East Door / of / Radio and Television Station / East Gate / South Procuratorate of Hangzhou City, Zhejiang Province.
Query_POS_Chunks	浙江省-ns / 杭州市-ns / 人民-n / 检察-vn / 北东-ns / 院侧-n / 广播-vn / 电视台-n / 东门-ns / 南-ns Zhejiang Province / Hangzhou City / People / Procuratorate / North East / of / Radio Television Station / East Gate / South Procuratorate of Hangzhou City, Zhejiang Province.
Candidates	浙江省人民北路路旁播州区人民检察院 People’s Procuratorate of Bozhou District, beside Renmin North Road, Zhejiang Province. 浙江省人民检察院 Zhejiang Provincial People’s Procuratorate. 浙江省浙江北路136号山东广播电视台 Shandong Radio and Television Station, No. 136 Zhejiang North Road, Zhejiang Province. 台州路1号杭州市拱墅区人民检察院 People’s Procuratorate of Gongshu District, Hangzhou City, No. 1 Taizhou Road.
Candidates_Geo_Chunks	浙江省-prov / 人民北路-road / 路旁-assist / 播州区人民检察院-poi Zhejiang Province / Renmin North Road / beside / People’s Procuratorate of Bozhou District. 浙江省-prov / 人民检察院-poi Zhejiang Province / Provincial People’s Procuratorate. 浙江省-prov / 浙江北路-road / 136号-roadno / 山东广播电视台-poi Zhejiang Province / Zhejiang North Road / No. 136 / Shandong Radio and Television Station 台州路-road / 1号-roadno / 杭州市-city / 拱墅区-district / 人民检察院-poi Taizhou Road / No. 1 / Hangzhou City / Gongshu District / People’s Procuratorate
Candidates_POS_Chunks	浙江省-ns / 人民-n / 北路-ns / 路旁-s / 播州-ns / 区-n / 人民检察院-nt Zhejiang Province / Renmin / North Road / beside / Bozhou / District / People’s Procuratorate. 浙江省-ns / 人民检察院-nt Zhejiang Province / Provincial People’s Procuratorate. 浙江省-ns / 浙江-ns / 北路-ns / 136-m / 号-m / 山东-ns / 广播-vn / 电视台-n Zhejiang Province / Zhejiang / North Road / 136 / No. / Shandong / Radio / Television Station 台州-ns / 路-n / 1-m / 号-m / 杭州市-ns / 拱墅区-ns / 人民检察院-nt Taizhou / Road / 1 / No. / Hangzhou City / Gongshu District / People’s Procuratorate

Table 11: A representative illustration sourced from the GeoTES dataset is provided. We are showcasing a subset of potential options in this context. The English was meticulously translated, as this information isn’t inherently present in our initial dataset.