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INNOVATION IN PHRASEOMATICS
DiCoP Project and DiCoP-Text Corpus for the Enrichment of Language Models and Automatic Translation

Abstract This article examines advances in phraseomatics (Chen, 2023) and digital phraseography through the DiCoP project and its DiCoP-Text corpus, aimed at enriching linguistic models and machine translation. The project evaluates the frequency of use of phraseological units (PUs) and improves their translation in different contexts, drawing on recent research in phraseotranslation (Sułkowska, 2022) and natural language processing (NLP). It emphasizes French-Chinese and Chinese-French language pairs. We integrated 549 PUs from the novel *The Three-Body Problem* by Liu Cixin for our tests. Various processes, such as tokenization, identification, alignment, and annotation, were used to improve the translation of PUs. DiCoP-Text, a comprehensive database including newspaper articles, literary works, and textbooks, aims to enhance the performance of language models (LMs).

Keywords DiCoP; DiCoP-Text; phraseomatics; phraseotranslation; digital phraseography; NLP; language models

1. Introduction: Digital (Meta)Phraseography and Phraseomatics

In the contemporary digital age, the field of computerized phraseography faces challenges, which highlights the emergence of a particular discipline: phraseomatics or computational phraseology (Chen, 2023). This article explores the intricacies between computer science and the analysis of phraseological units or PUs (Gonzalez-Rey, 2002; Bolly, 2011, p. 28) to understand the subtleties of semantics and the structure of expressions in a digital context. This emerging discipline highlights the challenges and opportunities inherent in the evolution of (meta)phraseography (Chen, 2022; 2023).

In this sense, we present the Dictionary and Corpus of Phraseology (DiCoP)[1] project we are currently developing. The main objective is to create an electronic dictionary of multilingual phraseology (currently French-Chinese and Chinese-French) concerning PUs. Thus, this article is concerned with Chinese into French and, more specifically, among the innovative aspects of this project, the DiCoP-Text, which will serve as a corpus for phraseotraduction.

Indeed, in French and Chinese, PUs are ubiquitous in daily use (Bolly, 2011), so their recognition poses a major challenge in natural language processing (NLP). The DiCoP project addresses this problem by creating a bilingual electronic dictionary

[1] To learn more about the architecture of the macrostructure and microstructure of this innovative DiCoP digital dictionary, we invite you to consult our work presented at the Asialex conference (Chen, 2023).

(with multilingual expansion envisaged) and developing a corpus of common PUs (e.g., collocations, idiomatic expressions, and proverbs). However, identifying PUs in a monolingual source text and translating them correctly for a parallel (bilingual) corpus constitutes a real challenge for automatic phraseotranslation (Sułkowska, 2022; Chen, 2022), especially since these expressions are numerous and possess metaphorical and opaque semantics (Gross, 1996).

2. Corpus of Phraseotraductology: DiCoP-Text

It is possible to determine corpus types depending on the characteristics of a corpus and the origin of its data. Bowker and Pearson (2002) distinguished the following corpus types: general/specialized, synchronic/diachronic, written/oral, and monolingual/bilingual. Monolingual corpora are comprised of data from just one language, while multilingual corpora are comprised of data from several languages and are either parallel or comparable.

DiCoP-Text refers to a collection of texts used to study PUs. This corpus contains a comparative component, in each language separately, sourced from various media (e.g., literary works, poetry, magazines, and newspapers) to analyze the usage and check the vitality (e.g., type and frequency) of PUs in a specific language. It also includes a parallel component (i.e., bilingual, primarily sourced from literary works, as other media lack existing translations) to enhance bilingual translations.

The collection and digital processing of texts are currently undergoing expansion. To illustrate the application of NLP in the DiCoP-Text project and analyze PUs, more precisely, *chéngyǔ*[2] corresponding to French idiomatic expressions, we selected a parallel corpus: the novel *The Three-Body Problem (三体 Sāntǐ)* by Liu Cixin, with its French translation. The novel comprises 186,079 words in the original Chinese version and 141,279 in the French version.[3]

3. DiCoP-Text and NLP: Analysis of Parallel Corpus Results

To develop the corpus and NLP, we started by processing various electronic or digitized file formats, converting them to conventional formats such as .txt. The corpus is designed to ensure its quality and relevance. We then analyzed the data to extract morphosyntactic and syntactic information, and automatically selected PUs from the corpora. We will now present our method and the steps of processing the corpus in a systematic and rigorous manner.

[2] "*Chéngyǔ* are polylexical sequences, fixed phrases, or short sentences that function as monolexical units within a sentence. Semantically, they are endowed with a specific, non-compositional meaning that cannot be directly deduced from the individual characters. Syntactically, their basic form, which most often follows a fixed quaternary (quadrisyllabic) rhythm and is divided phonetically and/or syntactically into two hemistichs, is conventional and unchanged for generations; hence the name chéngyǔ, meaning "ready-made expressions." Culturally, they convey the idiosyncrasies of a culture. Most often derived from classical literary language, they reflect an elegant and concise style and frequently contain strong allusive content" (Chen, 2021, p. 129). For example: *佛口蛇心 fókǒu-shéxīn* (Buddha's mouth, serpent's heart): "the mouth of a Buddha, the heart of a snake" (Prov.).

[3] For example, in French, "avoir la tête dans les nuages" (have your head in the clouds).

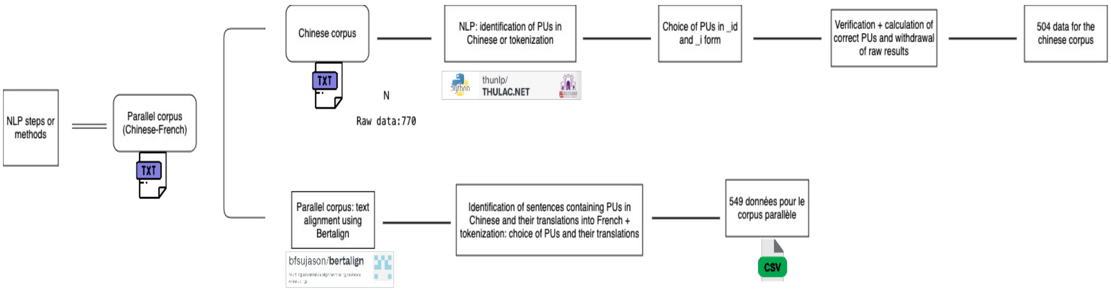

NLP steps or methods
Parallel corpus (Chinese-French)
TXT
Chinese corpus
TXT
N
Raw data:770
NLP: identification of PUs in Chinese or tokenization
python
thunlp/
THULAC.NET
Choice of PUs in _id and _i form
Verification + calculation of correct PUs and withdrawal of raw results
504 data for the chinese corpus
Parallel corpus: text alignment using Bertalign
bfsujason/bertalign
Identification of sentences containing PUs in Chinese and their translations into French + tokenization: choice of PUs and their translations
549 données pour le corpus parallèle
CSV

Fig. 1: NLP process followed for the parallel corpus

3.1 Performance and Evaluation of PU Identification in the Chinese Version with Thulac

For the Chinese analysis, we used the Thulac[4] tool with Python to identify *chéngyǔ*, which we marked as _i or _id to indicate they were idioms. Our results are described below.

Table 1: Chinese monolingual corpus performance and evaluation results

	Chinese PUs identified by Thulac			
Total	771			
Success rates	65.43% (504/771)			
Error rate	34.57% (267/771)			
	Form **_id** (567 PUs)	Form **_i** (204 PUs)		
	Correct	Error	Correct	Error
Number of IEs	321	246	183	21
Percentage	56.61 %	43.39%	89.71%	10.29%

We identified 771 instances marked as _id or _i. Of these, 504 were confirmed correct, with 267 errors not constituting PUs. Even with a success rate of approximately 65.43%, this tool greatly facilitated identification and tokenization at this stage. We also checked 66 idiomatic expressions (IEs) that the Thulac tool did not identify as PUs.

Furthermore, we observed repetitions in the IEs listed in this table. For example, the expression 一动不动 *yīdòngbùdòng* appeared seven times but was translated differently depending on the case, such as “ne bougeait plus” (no longer moved), “être immobiles” (to be still), and “resta immobile” (remained still), or it could be omitted in the translation depending on the specific context.

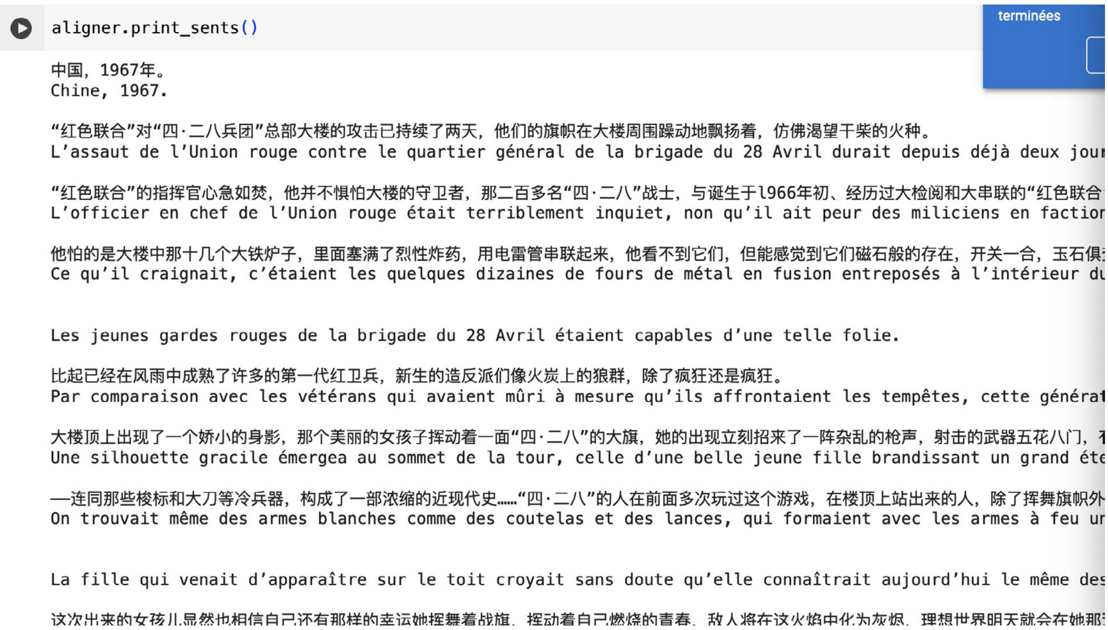
3.2 Data Alignment in Chinese and French

Data alignment in Chinese and French was conducted using the Bertalign[5] tool, which is known for its effectiveness in multilingual alignment. Bertalign

[4] http://thulac.thunlp.org/

[5] https://github.com/bfsujason/bertalign

achieves more accurate results than the traditional length-, dictionary-, or MT-based alignment methods (Thompson & Koehn, 2019). Bertalign identifies correspondences between words in both languages and facilitates the subsequent extraction of Chinese PUs and their French translations. Hence, the tool helps avoid literal translations of compositional expressions, which is a key challenge in machine translation.



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aligner.print_sents()
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中国，1967年。
Chine, 1967.

“红色联合”对“四·二八兵团”总部大楼的攻击已持续了两天，他们的旗帜在大楼周围躁动地飘扬着，仿佛渴望干柴的火种。
L’assaut de l’Union rouge contre le quartier général de la brigade du 28 Avril durait depuis déjà deux jou

“红色联合”的指挥官心急如焚，他并不惧怕大楼的守卫者，那二百多名“四·二八”战士，与诞生于l966年初、经历过大检阅和大串联的“红色联合
L’officier en chef de l’Union rouge était terriblement inquiet, non qu’il ait peur des miliciens en factio

他怕的是大楼中那十几个大铁炉子，里面塞满了烈性炸药，用电雷管串联起来，他看不到它们，但能感觉到它们磁石般的存在，开关一合，玉石俱
Ce qu’il craignait, c’étaient les quelques dizaines de fours de métal en fusion entreposés à l’intérieur d


Les jeunes gardes rouges de la brigade du 28 Avril étaient capables d’une telle folie.

比起已经在风雨中成熟了许多的第一代红卫兵，新生的造反派们像火炭上的狼群，除了疯狂还是疯狂。
Par comparaison avec les vétérans qui avaient mûri à mesure qu’ils affrontaient les tempêtes, cette généra

大楼顶上出现了一个娇小的身影，那个美丽的女孩子挥动着一面“四·二八”的大旗，她的出现立刻招来了一阵杂乱的枪声，射击的武器五花八门，
Une silhouette gracile émergea au sommet de la tour, celle d’une belle jeune fille brandissant un grand ét

—连同那些梭标和大刀等冷兵器，构成了一部浓缩的近现代史……“四·二八”的人在前面多次玩过这个游戏，在楼顶上站出来的人，除了挥舞旗帜外
On trouvait même des armes blanches comme des coutelas et des lances, qui formaient avec les armes à feu u


La fille qui venait d’apparaître sur le toit croyait sans doute qu’elle connaîtrait aujourd’hui le même de

这次出来的女孩儿显然也相信自己还有那样的幸运她挥舞着战旗，挥动着自己燃烧的青春，敌人将在这火焰中化为灰烬，理想世界明天就会在她那
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Fig. 2: Each sentence in Chinese and its French translation after alignment

After alignment, the results were evaluated for accuracy by analyzing selected sentences to guarantee the quality and reliability of the aligned data. Sentences containing these idioms and their translations were compiled in a CSV file for detailed analysis. By focusing on sentences containing PUs, we provided essential enriched context to enhance the efficiency of automatic translation. This targeted approach, recommended by Artetxe et al. (2018), eliminated the need for large parallel corpora. The PUs identified were associated with equivalents in the target languages and were classified by a confidence value.

These data were then passed on to our engineers for technical integration and optimization, ensuring efficient linguistic data management in a multilingual context.

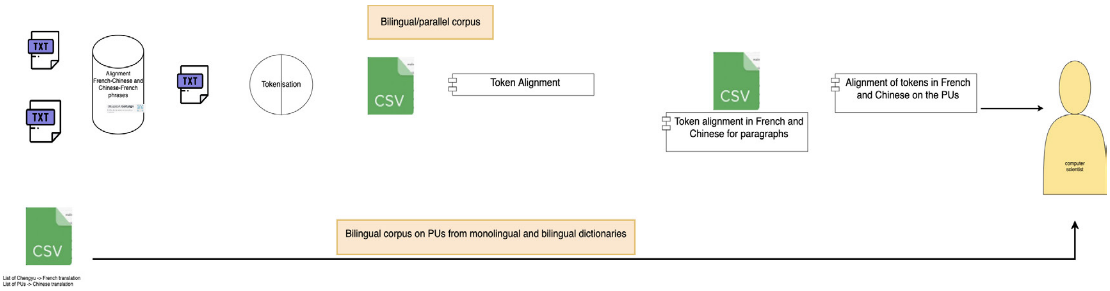
TXT
TXT
Alignment French-Chinese and Chinese-French phrases
TXT
Tokenisation
Bilingual/parallel corpus
CSV
Token Alignment
CSV
Token alignment in French and Chinese for paragraphs
Alignment of tokens in French and Chinese on the PUs
computer scientist
CSV
List of Chengyu -> French translation
List of PUs -> Chinese translation
Bilingual corpus on PUs from monolingual and bilingual dictionaries

Fig. 3: Processes from NLP to IT

4. DiCoP-Text for the Enrichment of Language Models and Automatic Translation: Phraséo – Tratuctologie et Informatique

Today, neural network technology is widely used in machine translation task, especially pre-trained models methods. Pre-trained models are trained with large-scale datasets and then fine-tuned for specific subtasks to achieve better performance. However, because of the dependency on pre-trained models for data and the lack of specific PU training data, the current pre-trained translation models faced challenges when the sentences contained PUs.

Thus, we proposed an approach to improve the translation of machine translation models' PUs.[6] First, we updated the vocabulary of the tokenizer of the pre-trained model based on PUs and then renewed the model's embedding layer so that the model could recognize PUs from the input context and produce the new token embedding. Then, we fine-tuned the model with individual PU data to improve its ability to embed the PUs into a semantic vector.

We proceeded to sentence-level training after the model could distinguish and embed individual PUs. We split the sentence data into training, validation, and test sets. With this idea, we tested if fine-tuning with the PU corpus could improve the machine translation model's ability to recognize and translate PUs at the sentence level.

Experiment, Results, and Analysis

We first extracted Chinese PUs from all datasets and compared each PU with the tokenizer of the language model. We added it if there was no corresponding item in the tokenizer's vocabulary while expanding the language model's embedding layer to initialize the weights of the added Chinese PUs. In the training phase, the model learned the embeddings of all Chinese PUs and the training sentence set. Then the model was tested on the test sentence set.

We selected these language models:[7] Mbart (Tang et al., 2020), M2m100 (Fan et al., 2021), Nllb (Costa-jussà et al., 2022), and Mrebel (Cabot et al., 2023). For metrics, we chose SacreBLEU (Post, 2018). The experiment corpus had 549 data items. We divided the corpus into training, validation, and test sets at a ratio of 6:2:2. Subsequently, 409 new tokens were added for each of the four language models to the tokenizer. In the training phase, we set learning to 4e-5 and the batch size to 8. For the translation task, we selected Chinese to French.

The results are shown in Table 2. The "Original model" and the "Fine-tuned model" designate the performance of the original and fine-tuned language models, respectively.

[6] The relevant code is available at the anonymous code repository: https://anonymous.4open.science/r/DiCo-C7BA

[7] The weights files of all the language models can be downloaded at this address separately: https://huggingface.co/Babelscape/mrebel-large, https://huggingface.co/facebook/mbart-large-50-many-to-many-mmt, https://huggingface.co/facebook/nllb-200-distilled-600M, and https://huggingface.co/facebook/m2m100_418M.

Table 2: The experimental results

Model	Original model	Fine-tuned model	Improved value
Mbart	2,0686	16,7191	14,6505
M2m100	4,9078	16,2120	11,3042
Nllb	4,6345	17,1385	12,5040
Mrebel	0,0131	7,1798	7,1667

Based on the experimental results, we noted that after fine-tuning, all language improved in translation performance, indicating that the introduction of PUs can help translation models better understand PUs. Although each fine-tuned model outperformed its original model, they all scored low. This phenomenon was related to the volume of the training data, as the pre-trained models needed a large corpus to enable them to learn as much as possible about the semantics of individual tokens under different contents. However, the dataset used in this experiment had only 549 items, which was insufficient. Therefore, the fine-tuning performance of the model will be further improved after the PUs corpus is expanded. Nonetheless, fine-tuning could not completely make up for the shortcomings of the original model. In addition to expanding the PU corpus, using the Chinese-French translation corpus of ordinary texts to improve the Chinese-French translation ability of the model can also improve the performance. We will use methods such as prompt engineering to explore the effects of corpus improvement in future work.

5. Conclusion

The first evaluation of the NLP tools in the DiCoP-Text project provided a detailed overview of the effectiveness of the DiCoP-Text corpus and the improved LMs. Our proposal aimed to improve LMs by integrating more fixed expressions and refining linguistic models for more accurate identification and translation of PUs. However, room for improvement exists:

1) In the future, we envision broader applicability of our DiCoP project. Indeed, expansion to other languages would strengthen its relevance and applicability across the IT language community. We also aim to provide more information, including details concerning user interfaces, accessibility, and integrating user feedback into ongoing development.

2) We studied the effect of fine-tuning the translation model using a PU corpus. This approach involved updating the tokenizer, training the model to integrate these PUs, refining the model from sentences containing them, and testing based on sentence-level data. The results indicated that fine-tuning the model with PUs could improve its translation capacity. However, given the limitations of the model and the corpus volume, additional efforts are necessary to refine its translation capacity. Thus, our future research will focus on expanding the corpus and improving the model's Chinese-French translation capability.

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