CMTS: A Dataset and Benchmark for Text Summarization of Minority Languages in China

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Abstract

Minority languages in China, such as Tibetan, Uyghur, and Traditional Mongolian, face significant challenges due to their unique writing systems, which differ from international standards. This discrepancy has led to a severe lack of relevant corpora, particularly for supervised tasks like text summarization. To address this gap, we introduce a novel dataset, Chinese Minority Text Summarization (CMTS), which includes 100,000 entries for Tibetan, and 50,000 entries each for Uyghur and Mongolian, specifically curated for text summarization tasks. Additionally, we propose a high-quality test set annotated by native speakers, designed to serve as a benchmark for future research in this domain. We hope this dataset will become a valuable resource for advancing text summarization in Chinese minority languages and contribute to the development of related benchmarks.

1 Introduction

Recently, the rapid development of large language models (LLMs) has been fueled by the availability of high-quality pre-training data. However, these advancements have primarily benefitted high-resource languages such as English and Chinese. In contrast, many languages with substantial user bases remain excluded due to the scarcity of suitable corpora, especially for specific tasks like *text summarization*. This exclusion poses challenges for both academic research and the practical application of AI technologies.

This paper focuses on underrepresented minority languages in China, including Tibetan, Uyghur, and Mongolian, which have rich linguistic and cultural significance but suffer from a lack of resources. Although these languages appear in multilingual datasets like OSCAR (Jansen et al., 2022) and CulturaX (Nguyen et al., 2024), quality issues limit their usefulness. As shown in Figure 1, there is a clear gap between the large speaker populations of these languages and the small amount of data

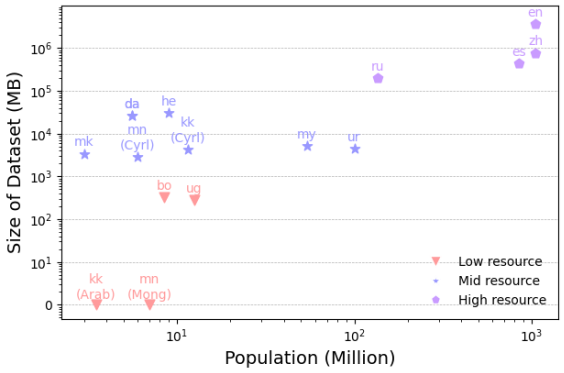

Figure 1: The relationship between population size and dataset size in OSCAR (y-axis, in MB) for various high-, middle-, and low-resource languages.

available in major corpora. Studies also reveal problems with data quality: Zhang et al. (2024) found that 34% of the Uyghur data in CulturaX contains Kazakh or Arabic texts, pointing to issues like language misidentification and noise. These challenges of data scarcity and quality undermine efforts to build effective natural language processing (NLP) systems for these communities.

Moreover, there is a complete lack of open-source datasets tailored for text summarization in these minority languages. This gap hinders the development of supervised methods and benchmarks for summarization tasks. To address this limitation, we introduce **Chinese Minority Text Summarization (CMTS)**, a novel dataset specifically designed for text summarization in Tibetan, Uyghur, and Mongolian. CMTS consists of **100,000 Tibetan samples** and **50,000 samples each** for Uyghur and Mongolian. In addition to the main dataset, we collaborated with native speakers of these languages to further ensure data quality. From the existing data, we selected **3,000 samples** for each language and conducted a detailed annotation process to evaluate the alignment and quality of the text summaries. These samples were reviewed by multiple annota-

tors for each language, and only the data deemed high-quality by consensus among native annotators was retained. This subset of data provides a reliable *benchmark* for future research, ensuring consistency and reproducibility in evaluating summarization models. By combining a large-scale dataset with carefully curated benchmark samples, CMTS bridges the gap in resources for text summarization in Chinese minority languages.

In summary, this paper makes the following key contributions:

- We present **CMTS**, a novel and large-scale open-source dataset specifically designed for text summarization in three Chinese minority languages: Tibetan, Uyghur, and Mongolian. We release this dataset under MIT license.

- We provide a carefully curated benchmark test set, annotated by native speakers, to ensure high-quality evaluation and support transparent, reproducible research in text summarization for Chinese minority languages.

By introducing CMTS, we aim to fill the resource gap and pave the way for advancing natural language processing research on underrepresented languages.

2 Data Sources

The Chinese Minority Text Summary (CMWS) dataset, proposed in this paper, is sourced from various online platforms in China, including government documents, broadcasts, and news articles (detailed list in Appendix A). We used web crawlers to collect the data, where the webpage title serves as the summary and the main text as the source content. To ensure data quality and reliability, we applied a thorough cleaning process, with the main methods outlined as follows:

- **Removal of Non-Textual Content**: We filtered out non-textual elements such as advertisements, pop-ups, navigation bars, and multimedia content (e.g., images, videos, and audio files). This ensured that only relevant text was retained.

- **Duplicate Detection and Removal**: We identified and removed duplicate entries to avoid redundancy in the dataset, which could potentially bias the summarization models.

- **Text Normalization**: We standardized the text by converting all characters to a uniform encoding format and removing any extraneous white spaces, special characters, or formatting inconsistencies.

- **Language Purity Check**: We conducted a language purity check to ensure that the collected texts were primarily in the target languages (Tibetan, Uyghur, and Mongolian). Non-target language content was filtered out to maintain linguistic integrity.

These steps were essential to ensure that the final dataset consisted of high-quality, relevant, and clean text that could be reliably used for text summarization tasks.

3 Annotation

After crawling the data, we further enhanced the quality of the three languages' evaluation set by native speaker annotation. For each language, we recruited two native speakers who helped assess the quality of the title-content matching. A total of 3000 randomly selected samples from the crawled data were annotated, with the task focused on evaluating how well the article titles matched the content of the articles.

3.1 Annotation Guidelines

The annotation process was designed to ensure the reliability and consistency of the evaluations. The annotators were provided with the following specific guidelines:

- **Task Objective:** Annotators were asked to assess the degree of relevance between the title and the content of the article and assign a score accordingly.

- **Title Evaluation:** Annotators were first asked to identify any issues between the title and the article content, such as:
  - *Incomplete Article:* whether the article content is incomplete, making it impossible for the title and content to match.
  - *Text Quality:* whether the title contains spelling, grammatical, or contextual errors that would significantly hinder its match with the article content.
  - *Other Issues:* whether there is any other noticeable discrepancies between the title and content, such as irrelevance.

Language	Size	Length In Token (Title/Content)	Length In Characters (Title/Content)
Tibetan	2901	12.3 / 376.7	74.0 / 1884.1
Mongolian	2931	27.2 / 429.8	134.3 / 2181.7
Uyghur	2950	30.2 / 815.7	91.5 / 3781.6

Table 1: Annotation Results for Valid Samples in the CMTS Dataset. The token length is counted using the CINO (Yang et al., 2022) tokenizer, while the character length is based on the raw character count for both title and content.

If no major issues were identified, the title-content match was considered "Normal."

- **Matching Score:** Annotators were instructed to rate the match based on how well the title corresponded with the article content. The scoring system was as follows:
  - **1 point:** Completely Mismatched (The title is entirely unrelated to the content).
  - **2 points:** Slightly Mismatched (The title is related to the content but does not align with the main theme).
  - **3 points:** Slightly Inaccurate (There is some connection, but it is not fully aligned).
  - **4 points:** Uncertain (The relationship between title and content is unclear or ambiguous).
  - **5 points:** Slightly Matched (There is a strong connection, but there are some inconsistencies).
  - **6 points:** Well Matched (The title matches the content with only minor discrepancies).
  - **7 points:** Fully Matched (The title perfectly corresponds to the content).

3.2 Consistency and Quality Control

To ensure consistency and accuracy across annotations, multiple annotators evaluated each article. The following steps were implemented to guarantee the quality of the annotations:

- **Consistency Check:** An annotation was considered invalid if the score differed by more than 2 points from the majority of annotators. Additionally, if an annotator's judgment deviated significantly from the majority opinion (e.g., the majority rated the title as "matching," but the annotator rated it as "not matching"), the annotation would be discarded.
- **Handling Invalid Annotations:** Invalid annotations were removed, and the annotators are incentivized to not produce such annotations.

3.3 Incentive System

To encourage careful and consistent annotation work, we implemented a reward-based incentive system:

- Scores **< 4** or **> 4** are considered as different tendencies:
  - Scores **< 4** indicate a *non-aligned* tendency.
  - Scores $\geq$ **4** indicate an *aligned* tendency.
- Annotation whose tendency aligns with the majority will receive **0.25 RMB**.
- Annotation that aligns with the majority tendency and furthermore deviates by no more than 1.5 points from the average score will receive an additional **0.25 RMB**.

Annotators were strongly encouraged to adhere to the guidelines to ensure the high quality and consistency of the dataset annotations.

3.4 Annotation Results

After removing the data flagged as mismatched or erroneous by the annotators, we retained the samples with an average score above 4. The final number of valid samples and the average length for each language are shown in Table 1.

In general, the data we retained showed a high degree of quality. Most of the remaining samples had scores of 7, with a small number scoring 6. This indicates that the majority of the collected data is of high quality and well-suited for text summarization tasks. These results suggest that the annotation process, guided by native speakers, was effective in ensuring the reliability and relevance of the data.

The average title and content lengths reflect the linguistic characteristics of these minority languages. For Tibetan, the average title is 12.3 tokens (74.0 characters) and the content is 376.7 tokens (1884.1 characters). Mongolian and Uyghur samples, however, show much longer lengths across both titles and contents.

4 Experiment

In this section, we evaluate some of the most popular models available for Tibetan, Mongolian, and Uyghur on CMTS, including finetuning small encoder-decoder models and few-shot evaluation of LLMs.

4.1 Experimental Settings

Fine-tuned Models: The small models, **cino-cum** (*which uses the **cino** (Yang et al., 2022) encoder, based on the XLM-R model tailored for Chinese minority languages, and a transformer decoder in a seq2seq architecture*) and **swcm** (Su et al., 2025) (*which is based on the same structure as cino-cum, but incorporates shared weight optimization across the encoder and decoder for improved performance across languages*), are fine-tuned on non-annotated data from the CMTS dataset. These models are then evaluated using high-quality annotated data to assess their summarization performance. The fine-tuning is conducted on raw, non-annotated data, while the evaluation is done using a set of annotated samples to measure the ROUGE-L scores.

Few-shot Models: The large models, **Qwen2.5-72B** (Yang et al., 2024) and **LLaMA3.1-70B** (Dubey et al., 2024) use a 2-shot learning paradigm, where two annotated samples are dynamically inserted as examples within the input of each annotated sample.

Detailed training configurations and hyperparameters are provided in Appendix B.

4.2 High-Quality Small Sample Experiment

Given that evaluating large models like **Qwen2.5-72B** and **LLaMA3.1-70b** with nearly 3,000 annotated samples per language is resource-intensive, we also selected a high-quality subset for evaluation to facilitate future works. Specifically, we chose the top 500 annotated samples based on evaluation scores to create a high-quality small sample version, enabling more efficient performance assessment while maintaining data quality.

Model	Size	bo	mn	ug
cino-cum	411M	0.20	0.12	0.9
swcm	457M	0.23	0.18	0.15
Qwen2.5	72B	0.24	0.32	0.29
LLaMA3.1	70B	0.34	0.30	0.35

Table 2: Model Parameters and ROUGE-L F1 Scores across all annotated data

Model	bo	mn	ug
cino-cum	0.21	0.13	0.10
swcm	0.23	0.17	0.14
Qwen2.5	0.24	0.29	0.34
LLaMA3.1	0.34	0.31	0.34

Table 3: ROUGE-L F1 Score in High-Quality data

4.3 Results and Discussion

The experimental results are summarized in Table 2, which presents the performance of the models on the CMTS dataset across the three languages: Tibetan (bo), Uyghur (ug), and Mongolian (mn). The fine-tuning results for the small models, **cino-cum** and **swcm**, show that both models achieved competitive ROUGE-L scores, demonstrating that fine-tuning with the CMTS dataset enables the models to effectively capture text summarization capabilities for all three languages. This indicates that the large amount of non-annotated data collected in the CMTS dataset plays a crucial role in enhancing model performance for these underrepresented languages.

For the large models, **Qwen2.5-72B** and **LLaMA3.1-70B**, the few-shot results, as shown in Table 2 and Table 3, reveal strong performance across both small and large sample tests. This demonstrates that the models exhibit high-quality summarization capabilities, regardless of the sample size, highlighting the effectiveness of using small annotated datasets for evaluating model performance. The ability of these models to perform well with just a few annotated samples supports the idea that the CMTS dataset, with its carefully curated annotated samples, can serve as a reliable benchmark for future research and evaluation in text summarization for minority languages.

Overall, both the fine-tuning and few-shot learning approaches contribute significantly to advancing text summarization for minority languages, and the CMTS dataset proves to be a valuable resource for further research in this area.

5 Limitations

Despite the significant contributions of the CMTS dataset in advancing text summarization for Chinese minority languages, several limitations remain. First, while the CMTS dataset represents a substantial effort to address the data scarcity issue for Tibetan, Uyghur, and Mongolian, the availability of high-quality linguistic resources for these languages is still limited compared to high-resource languages like English and Chinese. The scarcity of large-scale annotated datasets for other minority languages in China and beyond further highlights the need for continued efforts to expand the scope of language resources. Additionally, the current dataset focuses primarily on text summarization tasks, leaving other NLP applications underexplored. Future work will aim to address these limitations by expanding the dataset to include more minority languages and diversifying the types of NLP tasks supported. We also plan to collaborate with more native speakers and linguistic experts to enhance the quality and coverage of the dataset. By doing so, we hope to contribute to a more inclusive and comprehensive development of NLP research for underrepresented languages.

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A Dataset Details

A.1 1. Dataset Size

Table 4 shows the size of annotated and non-annotated data for each language in the CMTS dataset.

A.2 2. List of Crawled Websites

Table 5 lists the websites and URLs used for data crawling.

B Training Details

Fine-tune Training Details

Hardware: NVIDIA A5000 GPU, 24 GB RAM, Intel i7 CPU.

Software: Ubuntu 20.04, CUDA 11.7, PyTorch 2.3

Training Configurations

Local Batch Size: 20

Gradient Accumulation Steps: 4

Global Batch Size: 80

Epochs: 50

Optimizer: AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.999$

Learning Rate: 1e-4

Warm-up: Linear warm-up for the first epoch, gradually increasing the learning rate from 1e-5 to 1e-4.

Few-shot Training Details

In the few-shot setting, the model is provided with a prompt and a few examples to generate a task-specific output. For this task, the prompt is designed to help the model generate concise and accurate summaries in Tibetan, Uyghur, or Mongolian based on a provided passage and its title. The examples are structured to guide the model's behavior in generating the expected output.

Prompt

Based on the provided passage with title and content, generate a concise and accurate summary in {Tibetan/Uyghur/Mongolian}:

Example 1/2:
Content: Passage
Title: Title of the passage

Example 2/2:
Content: Passage
Title: Title of the passage

Task:
Content: Passage

The model generates a concise and accurate summary based on the given passage and title.

Language	Annotation Size	Non-Annotation Size
Tibetan (bo)	2901	100,000
Mongolian (mn)	2931	50,000
Uyghur (ug)	2950	50,000

Table 4: Dataset size for each language in CMTS.

Website Name	URL	Language
Qinghai Lake Website (Tibetan Version)	https://www.amdotibet.cn	BO
China Tibet News Network	https://tb.xzxw.com	BO
Bon Religion Website	http://www.himalayabon.com	BO
Kamba Satellite TV Network	http://tb.kangbatv.com	BO
Qinghai Tibetan Language Radio and TV Station	http://www.qhtb.cn	BO
China Tibetan Calligraphy Website	http://www.zgzzsfw.com	BO
Inner Mongolia Government Website	https://mgl.nmg.gov.cn	MN
Hulunbuir City Government Website	http://mgl.hlbe.gov.cn	MN
Xilingol League Government Website	http://mgl.zlq.gov.cn	MN
Ula'gae Government Website	http://mgl.wlgglq.gov.cn	MN
Chifeng City Government Website	http://mgl.chifeng.gov.cn	MN
Tongliao City Government Website	http://mgl.tongliao.gov.cn	MN
Aksu News Network	https://uy.aksxw.com	UG
Nur Network	https://www.nur.cn	UG
Tianshan Net	http://uy.ts.cn	UG
Xinjiang Government Website	https://uygur.xinjiang.gov.cn	UG
Xinjiang Daily Website	http://xjrbuy.ts.cn	UG

Table 5: List of websites used for data crawling.