A Semantic Uncertainty Sampling Strategy for Back-Translation in Low-Resources Neural Machine Translation

Yepai Jia[1], Yatu Ji[1,*], Xiang Xue[1], Lei Shi[2], Qing-Dao-Er-Ji Ren[1], Nier Wu[1], Na Liu[1], Chen Zhao[1], Fu Liu[1]
[1]Inner Mongolia University of Technology, China
[2]Inner Mongolia University of Finance and Economics, China
∗ **Correspondence**: mljyt@imut.edu.cn

Abstract

Back-translation has been proven effective in enhancing the performance of Neural Machine Translation (NMT), with its core mechanism relying on synthesizing parallel corpora to strengthen model training. However, while traditional back-translation methods alleviate the data scarcity in low-resource machine translation, their dependence on random sampling strategies ignores the semantic quality of monolingual data. This results in the contamination of model training through the inclusion of substantial low-quality samples in the generated corpora. To mitigate noise interference, additional training iterations or model scaling are required, significantly increasing computational costs. To address this challenge, this study proposes a Semantic Uncertainty Sampling strategy, which prioritizes sentences with higher semantic uncertainty as training samples by computationally evaluating the complexity of unannotated monolingual data. Experiments were conducted on three typical low-resource agglutinative language pairs: Mongolian-Chinese, Uyghur-Chinese, and Korean-Chinese. Results demonstrate an average BLEU score improvement of +1.7 on test sets across all three translation tasks, confirming the methods effectiveness in enhancing translation accuracy and fluency. This approach provides a novel pathway for the efficient utilization of unannotated data in low-resource language scenarios.

1 Introduction

The heavy reliance of NMT on large-scale parallel corpora significantly constrains performance improvement for low-resource languages (particularly minority languages), due to the difficulty in constructing high-quality bilingual datasets. In contrast, monolingual data has become a research focus given its accessibility, and methods leveraging monolingual resources to optimize model performance have been widely applied in low-resource scenarios (Edunov et al., 2018; Xu et al., 2022; Haddow et al., 2022; Ranathunga et al., 2023). Among these approaches, back-translationas a representative semi-supervised methodbreaks through the constraints of manual annotation by reversely generating pseudo-parallel data. It has been validated as a core strategy for enhancing translation quality (Sennrich et al., 2016a; Poncelas et al., 2018) and has become standard practice in building large-scale NMT systems due to its practicality (Siddhant et al., 2020; Huang et al., 2021).

Nevertheless, conventional back-translation implementations typically employ unfiltered monolingual corpora. While capitalizing on data abundance, this practice inevitably incorporates syntactically simplistic or semantically homogeneous sentencesa dual detriment that not only squanders computational resources but also introduces noise that undermines models' capacity to capture sophisticated linguistic patterns. Although recent studies (Edunov et al., 2018) have attempted to enhance output diversity through optimized beam search strategies (Meister et al., 2020), these methods remain insufficient in mitigating the inherent noise from semantically redundant training instances. This limitation manifests as constrained model generalization capabilities, exposing critical gaps in proactive quality screening mechanisms for corpus curation.

To address these issues, this study proposes a semantic uncertainty back-translation sampling strategy. By identifying monolingual sentences with high semantic uncertainty and leveraging them for back-translation, this method efficiently improves model performance and mitigates the scarcity of low-resource corpora. Large-scale experiments demonstrate that the proposed uncertainty-based sampling strategy for self-training significantly outperforms random sampling. Extensive analysis of the generated outputs validates our claims and contributes to existing research in the following ways:

Demonstrates the necessity of semantic uncertainty sampling for back-translation.

Proposes a semantic uncertainty-aware back-translation sampling strategy, empirically validated for feasibility in low-resource language scenarios.

Transfers semantic information from the target language to the source language in low-resource settings, reducing the translation models reliance on parallel corpora.

2 Related Work

The development of data augmentation techniques for low-resource neural machine translation has seen researchers continuously overcome the bottleneck of parallel corpora through multi-dimensional innovations. Back-translation has been extensively explored: The monolingual data back-translation paradigm pioneered by Sennrich et al. (Sennrich et al., 2016b) established the foundation for pseudo-data generation. Subsequently, Daimeng et al. (Wei et al., 2023) introduced text style transfer technology (TST BT) to align generated data more closely with natural language distribution characteristics. Concurrently, Jiao et al. (Jiao et al., 2021) proposed a self-training strategy based on uncertainty probability from bilingual dictionaries, enhancing the model's predictive capability for low-frequency words by filtering high-uncertainty monolingual sentences. Wei et al. (Wei et al., 2022) proposed an adjacency semantic space modeling framework, which dynamically partitions semantic boundaries and selects high-quality samples through a Gaussian mixture cyclic chain algorithm, achieving systematic optimization.

For neural machine translation of low-resource language pairs, researchers address challenges of corpus scarcity and morphological complexity through multi-dimensional technological innovations. In Mongolian-Chinese translation, Ji et al. (Ji et al., 2019) enhanced model robustness by injecting Mongolian morphological noise via an adversarial training framework. Zhang's team(Zhang et al., 2023) optimized document-level context modeling through dual encoders with dynamic caching mechanisms. Sun et al.(Sun et al., 2021) combined back-translation with a dual-learning framework, achieving a 22% improvement in translation robustness. In Uyghur-Chinese translation, Feng et al.(Feng et al., 2023) designed an ensemble pruning algorithm based on back-translation to balance resource consumption and performance, while Yan et al. (Yan et al., 2024)improved Uyghur-to-Chinese translation performance by leveraging zero-resource transfer learning in multilingual translation models. For Korean-Chinese translation, Li et al. (Li et al., 2023) proposed the LW-Transformer model incorporating pre-normalization and localized self-attention mechanisms, which significantly improved Sino-Korean machine translation performance. These approaches synergistically advanced the practical application of low-resource translation technology through multi-level system collaboration.

At the foundational architecture level, the evolution of cross-lingual pretraining models has injected new momentum into low-resource language research. Although general models like XLM-R (Conneau et al., 2020) excel in multilingual tasks, their support for Chinese minority languages remains limited. The CINO model (Yang et al., 2022), through secondary pretraining on corpora of Tibetan, Mongolian (Uyghur script) and Uyghur , achieved a 13% Macro-F1 improvement over baselines, providing critical infrastructure for low-resource language studies. These advancements jointly enhance the robustness and domain adaptability of translation models in resource-constrained scenarios.

The performance enhancement of low-resource NMT remains constrained by three factors: agglutinative morphological structures, free word-order characteristics, and scarce parallel corpora. While existing methods demonstrate commendable results in specific domains, two critical limitations persist: (1) Traditional data filtering strategies fail to effectively capture the semantic complexity of low-resource languages; (2) Current evaluation systems lack fine-grained quantitative analysis of translations. To address these issues, this study proposes semantic uncertainty sampling, which optimizes training sample selection through dynamic evaluation of uncertainty distributions in source-target semantic spaces, while employing multiple evaluation metrics to comprehensively assess model performance.

3 Methodology

As proposed by Zhou et al. (Zhou et al., 2019), the complexity of parallel corpora can be quantified by aggregating the translation uncertainty across all source sentences. Formally, for a source sentence x,

the translation uncertainty of its selected translation y can be formulated as the conditional entropy:

$$\mathcal{H}(\mathrm{Y}|\mathrm{X}=\mathrm{x}) = -\sum_{\mathrm{y}\in\mathcal{Y}} p(\mathrm{y}|\mathrm{x}) \log p(\mathrm{y}|\mathrm{x}) \quad (1)$$

$$\approx \sum_{t=1}^{T_x} \mathcal{H}(y|x=x_t) \quad (2)$$

Here, T_x denotes the length of the original sentence, where X and Y represent the random variables for source-language and target-language sentences respectively. $\mathcal{X}$ and $\mathcal{Y}$ denote the sets of all possible source-language and target-language sentences, while x and y represent specific source and target sentence sequences in their concrete forms, with x and y denoting complete sentence instances. x_t indicates the t token of the sentence. Generally, a higher $\mathcal{H}(\mathrm{Y}|\mathrm{X}=\mathrm{x})$ suggests that the source sentence x has more potential translation candidates. Equation (2) estimates the translation uncertainty of source sentences using all possible translation candidates in parallel corpora. However, due to the lack of corresponding translation candidates, this approach cannot be directly applied to sentences in monolingual data.

To address this limitation, Jiao et al. (Jiao et al., 2021) utilized authentic parallel corpora to estimate the target word distribution $P(y|x)$ conditioned on each source word x. This distribution is then employed to quantify the translation uncertainty of monolingual instances. Furthermore, the process incorporates bilingual dictionaries as reference knowledge to measure the uncertainty of monolingual sentences.

Although Jiao's method provides a partial solution, it still has limitations. In our experiments, the lack of sufficient parallel corpora makes obtaining precise translation probabilities extremely difficult, directly resulting in the loss of critical information during computation. These factors collectively constrain the effectiveness of improving translation quality through alignment methods alone.

Therefore, this paper employs multilingual models to directly estimate word-level translation distributions. By introducing semantic similarity to refine translation probabilities, we use the model to generate vectorized representations of the source word x and candidate target word y. The formula is extended as:

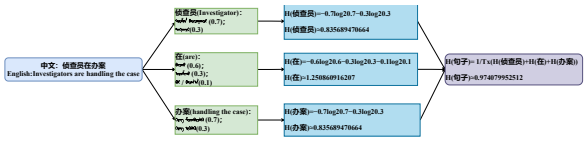


Figure 1: Graph of semantic uncertainty computation

$$\mathcal{H}_{\text{sem}}(\mathrm{x}) = -\frac{1}{T_x}\sum_{t=1}^{T_x}\sum_{i=1}^{y_i} q_{t,i} \log q_{t,i} \quad (3)$$

Here, $q_{t,i}$ is an abbreviation for $p_{\text{sem}}(y_i \mid x_t)$ and H_{sem} denotes the semantic uncertainty on the source-language sentence x. For each source word x, the semantic similarity of the target word y is transformed into a probability:

$$q_{t,i} = p_{\text{sem}}(y_i \mid x_t) = \frac{s(x_t, y_i)}{\sum_{y'\in\mathcal{Y}} s(x_t, y')} \quad (4)$$

Where $s(x_t, y_i)$ denotes the semantic similarity score between the source term x_t and target termy_i, $\mathcal{Y}$ represents semantically similar lexical items in the candidate targets. $\sum_{y'\in\mathcal{Y}} s(x_t, y')$ indicates the summation of semantic similarity scores over all candidate target terms $s(x_t, y_i)$, used for normalization.

As shown in Figure 1, a cross-lingual model was used to calculate the semantic similarity between the Chinese sentence "侦查员在办案" (lit. "investigators are handling the case") and its Mongolian counterpart. The process first involved detailed tokenization of the sentences, followed by entropy calculations for individual words to quantify internal uncertainty. The total sentence information entropy was approximately 0.974, indicating that the original sentence possesses a certain level of complexity and uncertainty.

The sampling strategy based on semantic uncertainty in Equation (3) exhibits a preference for monolingual sentences with relatively higher uncertainty. To maintain data diversity while mitigating the risk of dominance by overly uncertain sentences, we perform monolingual sampling according to an uncertainty distribution that penalizes maximum uncertainty. Specifically, the sampling probability is governed through the configuration of two hyperparameters as follows:

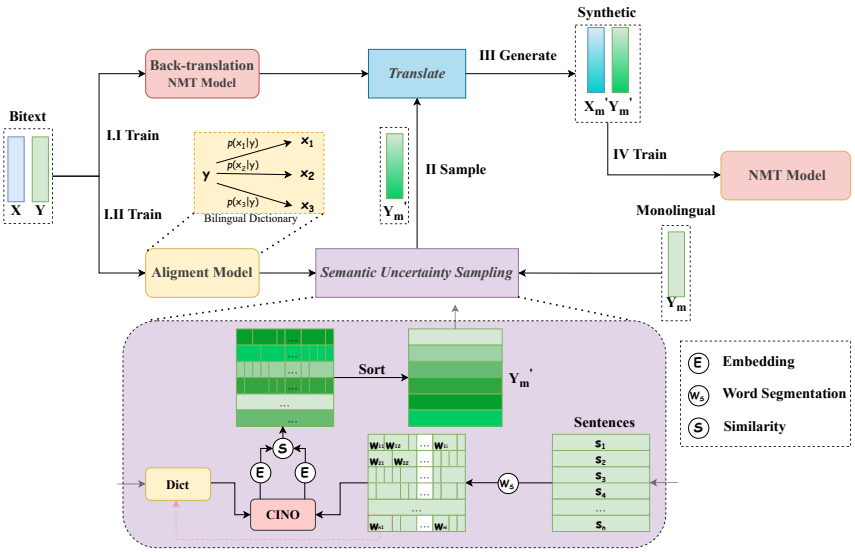


Figure 3: Semantic uncertainty sampling structure diagram: The proposed framework for self-training sampling based on semantic uncertainty is illustrated in the figure. The yellow and purple sections represent the methods integrated into the standard self-training framework. "Bitext", "Monolingual" and "Synthetic" denote authentic parallel data, monolingual data, and synthetic parallel data, respectively.

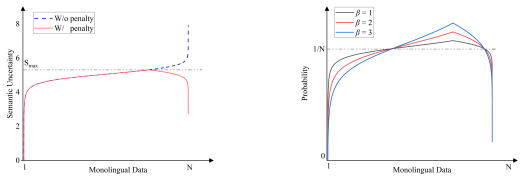
$$p = \frac{[\alpha \cdot H_{\text{sem}}(\text{x})]^{\beta}}{\sum_{\mathcal{M}_x} [\alpha \cdot H_{\text{sem}}(\text{x})]^{\beta}}, \tag{5}$$

$$\alpha = \begin{cases} 1, & H_{\text{sem}}(\text{x}) \leq H_{\max} \\ \max\left(\dfrac{2H_{\max}}{H_{\text{sem}}(\text{x})} - 1,\ 0\right), & \text{else} \end{cases} \tag{6}$$

The primary objective of the formula is to identify and penalize samples exhibiting abnormally high uncertainty, where $H_{\max}$ represents the upper limit of acceptable semantic uncertainty. $\mathcal{M}_x$ denotes an additional monolingual corpus dataset. The parameter α penalizes excessive uncertainty exceeding the maximum threshold U_{max}, while β adjusts the distribution such that larger β values assign greater probability mass to sentences with higher uncertainty.

The aforementioned methods only address the discussion of the sampling process and do not encompass the complete back-translation procedure.

As shown in Fig.2, the model's performance under different monolingual data scales is demonstrated. When applying the penalty term (W/ penalty) with β=3, the model exhibits lower semantic uncertainty and higher probability increase rate under small data volumes; however, performance degradation occurs with increasing data due to over-regularization. In contrast, when β=1, the model effectively balances generalization capability and uncertainty control through gradual probability variations and stable regularization strength. This indicates that the β value not only affects model stability on small datasets, but also determines its overfitting risk and performance on large datasets, highlighting β's pivotal role in regulating penalty term intensity.



(a) Monolingual uncertainty probability distribution graph.

(b) Sampling probability distribution graph.

Figure 2: Comparison of uncertainty and probability distributions.

We apply the aforementioned sampling method to back-translation. The paper primarily comprises the following key steps: first, training a reverse NMT model on real parallel data; second, aligning words in the alignment model, computing semantic similarity, and sampling monolingual sentences based on semantic uncertainty; third, translating the sampled monolingual sentences using the reverse NMT model to generate synthetic parallel data; and finally, training a new NMT model on the combined synthetic and real parallel data. Figure 3 illustrates

the framework of our semantic uncertainty-based sampling approach.

4 Experiments

4.1 Dataset

In this experiment, the research group utilized a Mongolian-Chinese NMT corpus comprising 1.2 million sentence pairs. The corpus spans multiple domains: 300k CCMT evaluation benchmarks, 200k government documents, 300k legal statutes, 50k historical archives, 100k specialized articles, daily conversational texts and other fields.. Additionally, the test set incorporates a challenging and representative 50k bilingual legal question-answer dataset (Zhaomuerlige and Wang, 2024).Throughout the experiment, all corpora were tokenized using the Moses scripts. Sentences with lengths between 1 and 1000 tokens were retained from the original corpus. Subsequently, BPE (Sennrich et al., 2016b) with 40K merge operations was applied to enhance vocabulary representation efficiency and flexibility.

The monolingual Chinese corpus used for sampling tasks was sourced from the WMT2024 news dataset (Kocmi et al., 2024), which contains over 5 million sentences crawled in 2023.

To validate the generalizability and adaptability of the semantic uncertainty sampling method across low-resource language translation tasks, this study extended experiments beyond Mongolian-to-Chinese to include Korean-to-Chinese and Uyghur-to-Chinese translation tasks. This cross-lingual design ensures consistent performance across diverse language pairs.

For the Korean-to-Chinese task, the CCAligned dataset (El-Kishky et al., 2020) was employed, containing approximately 1.02 million parallel sentences. In the Uyghur-to-Chinese task, a dataset with 600,000 parallel sentences was utilized.

4.2 Model

This study employs a standard TRANSFORMER architecture (Vaswani et al., 2017) as the core framework, comprising 6-layer stacked encoder modules and 6-layer symmetrical decoder modules. The implementation specifies a word embedding dimension of 512, with the feed-forward network hidden layer dimension expanded to 2048. Each attention sublayer incorporates 8 parallel attention heads. The system was deeply customized through the Fairseq (v0.10.2) open-source framework (Ott et al., 2019), strictly adhering to the TRANSFORMER_BASE parameter configuration scheme proposed by Vaswani et al. (Vaswani et al., 2017) (2017).Deployed on an NVIDIA GeForce RTX 3090 GPU (24GB VRAM) using PyTorch 1.9, the single-GPU training environment employed a mixed-precision training strategy to optimize VRAM utilization. Validation was performed after each epoch, with the best-performing intermediate model on the validation set retained as the final model.

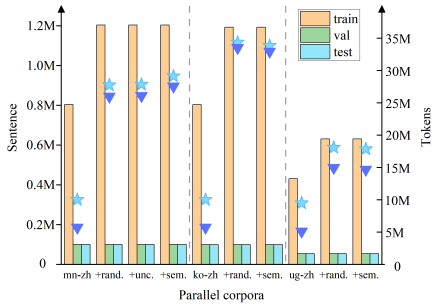


Figure 4: Parallel corpus diagram: The scale of the corpora used in the experiments is shown in the figure. The three sections separated by dashed lines represent the mn-zh, ko-zh, and ug-zh parallel corpora, respectively. The bar charts represent the number of sentences, while the (pentagram) and (triangle) markers denote the number of tokens in the training sets.

4.3 Evaluation Metrics

Within our research framework, to ensure experimental objectivity and reliability while providing a solid reference for subsequent studies, we selected multiple evaluation metrics to quantify machine translation system performance. Specifically, we employ the sacreBLEU (Post, 2018) tool to compute BLEU (Bilingual Evaluation Understudy) (Papineni et al., 2002) scores as the primary metric, supplemented by CHRF (Character n-gram F-score) (Popović, 2015) and TER (Translation Edit Rate) (Snover et al., 2006).

4.4 Experimental Results and Analysis

As shown in Figure 4, this chart illustrates sentence and word count distributions across Mongolian-Chinese (mn-zh), Korean-Chinese (ko-zh), and Uyghur-Chinese (ug-zh) parallel corpora. After applying three augmentation methods (random sampling, uncertainty-aware sampling, and semantic uncertainty-aware sampling), training sets show varying scale expansions. For example, mn-zh increased sentences from 0.8M to 1.2M and words

System	Model	BLEU-4		sacreBLEU		chrF		TER	
(Zhang et al., 2024)	BITEXT	–		32.73		–		–	
	+Easy Data Augmentation	–		33.15		–		–	
	+Back Translation	–		33.57		–		–	
	+ Iterative Back-Translation	–		34.55		–		–	
(Wei and Ren, 2024)	BITEXT	–		32.48		–		–	
	+Methods(Dropout)	–		33.93		–		–	
	+Methods(Swap)	–		35.16		–		–	
	+Methods(Replacement)	–		35.27		–		–	
		16w	Law	16w	Law	16w	Law	16w	Law
	BITEXT(mn-zh)	27.87	15.48	33.8	23.6	31.1	22.0	64.1	66.0
This Work	+40w randomSamp	31.34	22.17	35.4	29.3	32.8	26.7	60.3	59.1
	+40w UncSamp	31.12	**22.64**	35.2	29.7	32.7	27.0	60.3	58.8
	+40w SemUncSamp(ours)	**31.48**	22.38	**35.8**$^{\uparrow}$	**31.1**$^{\uparrow}$	**33.3**$^{\uparrow}$	**28.4**$^{\uparrow}$	**59.5**$^{\uparrow}$	**57.7**$^{\uparrow}$

Table 1: Model Performance Scores on 16w and Law Domains: "16w" represents a test set of 160,000 sentences selected from the original Mongolian-Chinese parallel corpus, strictly independent of the training and validation sets; "law" denotes the legal Q&A dataset(Zhou et al., 2019). Lower TER indicates better performance. "$^{\uparrow}$" indicates statistically significant improvement over randomSamp with $p < 0.01$.

from 1.1M to 2.8M. The chart highlights corpus size variations across datasets.

This study employed the experimental configuration described in Section 4.2, using the TRANSFORMER_BASE model as the base architecture. It was compared against several sampling methods: Baseline, Random Sampling, Uncertainty Sampling, and our proposed Semantic Uncertainty Sampling. The experiments aimed to evaluate the impact of different sampling strategies on machine translation performance for the Mongolian dataset.

According to Table 1, the model performance comparison among three research teams in machine translation tasks is evaluated using BLEU-4, sacreBLEU, chrF and TER metrics. Zhang(Zhang et al., 2024) employed progressive data augmentation techniques (e.g., iterative back-translation) on the BITEXT model to enhance sacreBLEU from 32.73 to 34.55. Wei(Wei and Ren, 2024) achieved the highest sacreBLEU score of 35.27 among compared methods through regularization-based model improvements using replacement strategies. Our experiments on general domain (16w) and legal domain (Law) datasets revealed insufficient domain adaptability of the baseline model, manifesting in a BLEU-4 of merely 15.48 and a TER as high as 66.0 for Law dataset. The proposed Semantic-UncSamp method optimized sampling strategies to achieve comprehensive optimal performance on Law dataset with sacreBLEU 31.1, chrF 28.4 and TER 57.7, demonstrating dual improvements in fluency and accuracy for specialized domain translation, particularly validating its effectiveness in vertical fields like legal translation. Furthermore, Uncertainty Sampling (UncSamp) elevated BLEU-4 to 22.64 on Law dataset, indicating the superiority of flexible sampling strategies over conventional data augmentation methods. Collectively, our work demonstrates that focused optimization of sampling strategies can more significantly enhance translation performance compared to traditional data augmentation approaches, effectively balancing semantic diversity enhancement with noise reduction, thereby providing an optimized direction for machine translation model refinement.

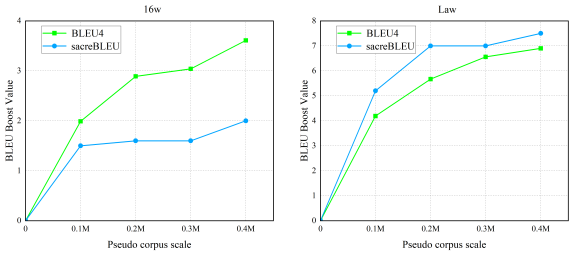


Figure 5: The Impact of Different Scales of Pseudo Corpora in Mixed Corpora on Translation Results

Figure 5 demonstrates the impact of back-translation data scale on model performance in Mongolian-to-Chinese translation. Initially (pseudo-corpus scale=0), the model achieves baseline values of 15.48 BLEU4 and 23.6 sacreBLEU. With pseudo-corpus expansion, performance improves significantly: at 0.1M scale, both metrics show rapid enhancement, indicating that minimal

back-translation data suffices for improvement; when reaching 0.4M scale, BLEU4 rises to approximately 22.38 with concurrent sacreBLEU growth. Overall, model capability strengthens continuously with pseudo-corpus enlargement, confirming back-translation's effectiveness in low-resource scenariosmost pronounced in small-data conditions, while performance gains gradually stabilize yet maintain steady progression with increased data volume.

	Seed	BLEU-4	sacre-BLEU	chrF	TER
Law	42	22.38	31.1	28.4	57.7
	3048	22.05	31.1	28.3	57.9
	114514	22.45	31.1	28.4	57.6
16w	42	31.48	35.8	33.3	59.5
	3048	31.61	35.8	33.2	60.1
	114514	31.46	35.4	32.8	60.4

Table 2: Experimental results of dataset partitioning under different random seeds

To validate whether different data partitioning strategies affect model performance, Table 2 presents control experiments using three independent random seeds (42/3048/114514). For the Law dataset, the standard deviation of BLEU-4 is 0.20 while sacre-BLEU remains constant. On the 16w dataset, TER exhibits a fluctuation range of 0.9 (59.5-60.4) and chrF shows a narrow range of only 0.5. This cross-dataset metric stability ($p > 0.05$ in ANOVA) confirms the model's robustness to training data partitioning and provides statistically significant support for experimental reproducibility.

Mongolian	RefTrans	BITEXT	SemUnSamp
[illegible]	律师协会就处理强奸案问题发布了指导原则。 The Bar Association has issued guidelines to address the issue of handling rape cases.	工会对解决暴力犯罪问题的指导原则已经确立。 The labor union has established guidelines for resolving violent crime issues.	律师协会就处理强奸罪问题提出了指导原则。 The Bar Association has proposed guidelines to address the issue of handling the crime of rape.
[illegible]	向这个国家进口武器是非法的。 Importing weapons into this country is illegal.	给这个国家带来武器是不合法的。 Bringing weapons to this country is not lawful.	向这个国家提供武器是非法的。 Providing weapons to this country is illegal.

Table 3: Comparative Example Illustration of Mongolian-Chinese Translations

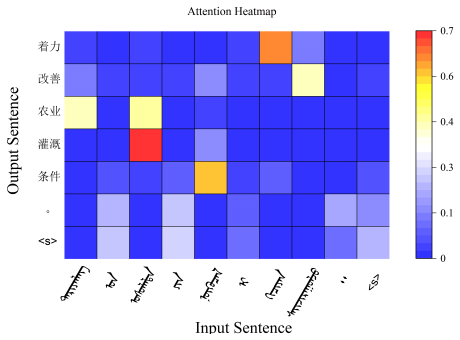


Figure 6: Attention heatmap

Figure 7: Position score map

As shown in Table 3, the baseline model erroneously translates "律师协会" (Bar Association) as "工会" (labor union), generalizes specific case types like "强奸案" (rape case) to "暴力犯罪" (violent crime), and employs weak-action verbs like "确立" (establish) instead of active equivalents for "发布" (issue). In contrast, the SemanticUnSamp model demonstrates superior performance through precise retention of core terminology such as "律师协会" (Bar Association) and "强奸罪" (rape case), along with context-appropriate verb selections like "提出" (propose) that maintain logical framework integrity. However, discrepancies persist in handling action verbs like "进口" (import), where substitutions such as "提供"(bring) fail to convey original semantic implications. While outperforming the baseline in professional terminology accuracy and informational completeness, this model still requires further optimization in verb precision to bridge the gap with reference translations.

To visually represent the distribution of attention weights between source and target languages in translation, this paper employs heatmaps (Figure 6) to demonstrate decoding performance. Color intensity reflects candidate word probabilities: darker hues indicate higher probabilities. Highlighted regions reveal successful alignment of words/phrases between input and output sequences. For instance, high alignment accuracy is observed between "[illegible]" ("着力", effort) and "[illegible]" ("灌溉", irrigation), predicting subsequent translations consistent with reference translations.

Further quantitative analysis of lexical impor-

Metric	Uyghur-to-Chinese			Korean-to-Chinese		
	BITEXT	+40w RandSamp	+40w SemUncSamp(ours)	BITEXT	+40w RandSamp	+40w SemUncSamp(ours)
BlEU-4	29.54	30.9	**31.08**	36.80	37.08	**37.16**
Precision 1-gram	60.9	62.2	**62.2**	59.7	60.2	**60.9**
Precision 2-gram	35.0	36.6	**36.7**	41.7	41.9	**42.8**
Precision 3-gram	23.4	24.8	**24.9**	34.2	34.2	**35.3**
Precision 4-gram	16.7	17.8	**18.0**	29.5	29.5	**30.5**
sacreBLEU	35.7	36.9	**37.6**	40.2	40.9	**41.4**
chrF	32.8	33.9	**34.9**	45.0	45.4	**46.0**
TER	58.4	57.3	**56.4**	57.1	56.6	**55.7**

Table 4: The comparative results of various model evaluation metrics on Uyghur-to-Chinese and Korean-to-Chinese translation datasets. Notably, lower TER score indicates superior model performance.

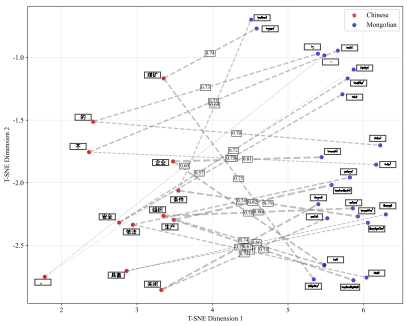


Figure 8: Chinese vs. Mongolian Text Embeddings in t-SNE Space

tance in the sentence “努力改善农业灌溉条件。” is conducted through positional score maps (Figure 7). Results show: “改善”(improve) and “灌溉” (irrigation) achieve significant positional scores (P=-0.07, probability≈0.93), indicating highest predictive confidence; while “条件”(conditions) receives a lower score (P=-0.24, probability≈0.78), with reduced confidence in its Mongolian translation “[illegible]”. Nevertheless, the overall translation quality remains high. Potential discrepancies may stem from ambiguous semantic boundaries of “条件”(conditions) as supplementary content or diverse bilingual alignment patterns.

This study employs t-SNE technique to perform dimensionality reduction visualization on Chinese-Mongolian bilingual word embedding spaces, generating a 2D mapping atlas (Figure 8) that reveals cross-lingual semantic alignment characteristics. Results indicate significant clustering between Chinese (red) and Mongolian (blue) lexical items in low-dimensional space, encompassing cross-lingual mappings of both domain-specific terms and high-frequency lexical items. The semantically correlated networks connected by gray dashed lines (annotated with confidence levels) further quantitatively validate cross-lingual lexical similarities, providing intuitive evidence for machine translation model evaluation.

This study conducted supplementary comparative experiments targeting Korean-to-Chinese and Uyghur-to-Chinese translation tasks to further validate the performance of the proposed sampling strategy across different language pairs.

Experimental results (Table 4) demonstrate the superiority of the semantic uncertainty-aware sampling strategy in Uyghur-Chinese and Korean-Chinese translation tasks. The method effectively improves translation quality even in linguistically divergent contexts, such as those involving substantial syntactic and lexical disparities. For the Uyghur-Chinese task, the approach outperforms baseline models across all metrics (BLEU, chrF, and TER). In the Korean-Chinese task, leveraging 400k semantically uncertain training instances achieves state-of-the-art performance, including a BLEU4 score of 37.16 and optimal sacreBLEU/chrF values. These findings confirm the strategy’s capability to model cross-lingual semantic correspondences, significantly enhancing translation robustness in morphosyntactically distinct language pairs.

Finally, to quantify the benefits of translation performance improvement, we introduce the cost-effectiveness ratio (Incremental Cost / BLEU). In the legal domain of Mongolian-Chinese translation, the semantic uncertainty sampling strategy achieved a 7.5 BLEU improvement with an incremental cost of 102,926 seconds, resulting in a cost-effectiveness ratio of 13,724 seconds/BLEU. This represents a 22.4% increase in efficiency compared to random sampling. In the general domain, however, the same strategy yielded only a 2.0 BLEU improvement, with a cost-effectiveness ratio of 51,463 seconds/BLEU. This reveals that legal text exhibits significant sensitivity to data optimization:

the BLEU gain per unit cost is 3.75 times that of the general domain. Particularly noteworthy is that when upgrading from random sampling to semantic uncertainty sampling, only an additional 1.26% of training time was required to achieve a marginal BLEU gain of 1.8. The cost-effectiveness ratio at this stage reached 4.5 times the efficiency of the corresponding stage in the general domain.

5 Conclusion

In this work, addressing the dependency of back-translation tasks on high-quality data in NMT, this paper proposes a semantic uncertainty-based sampling strategy. By identifying and sampling monolingual data with higher semantic uncertainty, this method enhances the quality of training data in the back-translation process. Experimental results demonstrate that compared to traditional random sampling approaches, the semantic uncertainty-based sampling strategy achieves improved translation quality. It ensures that the data used in back-translation is both sufficient in quantity and higher in quality, enabling targeted resolution of the model's weaknesses and blind spots.

6 Limitations

The experiment relies on advanced cross-lingual models; however, for low-resource languages, their training data volume is relatively limited, which may lead to insufficient generalization capabilities of the models. Consequently, how to enhance the performance of these models on specific low-resource languages has become a pressing issue to be addressed.

7 Acknowledgements

This study is supported by the National Natural Science Foundation of China (62206138, 62466044), Inner Mongolia Natural Science Foundation (2024MS06009,2024MS06017,2024QN06021), Research Program of Science and Technology at Universities of Inner Mongolia Autonomous Region (NJZZ23081), Inner Mongolia Basic research expenses (ZTY2025072), and Science Research Foundation of Inner Mongolia University of Technology (BS2021079).

References

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451.

Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. Understanding back-translation at scale. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 489–500.

Ahmed El-Kishky, Vishrav Chaudhary, Francisco Guzmán, and Philipp Koehn. 2020. CCAligned: A massive collection of cross-lingual web-document pairs. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing*, pages 5960–5969.

Xiao Feng, Ya-Ting Yang, Rui Dong, and Bo Ma. 2023. Uyghur and chinese machine translation system based on ensemble pruning. *Manufacturing Automation*, 45(2):69–73.

Barry Haddow, Rachel Bawden, Antonio Valerio Miceli Barone, Jindich Helcl, and Alexandra Birch. 2022. Survey of low-resource machine translation. *Computational Linguistics*, 48.

Guoping Huang, Lemao Liu, Xing Wang, Longyue Wang, Huayang Li, Zhaopeng Tu, Chengyan Huang, and Shuming Shi. 2021. Transmart: A practical interactive machine translation system. *Computing Research Repository*. ArXiv:2105.13072, Version 1.

Yatu Ji, Hongxu Hou, Chen Junjie, and Nier Wu. 2019. Improving Mongolian-Chinese neural machine translation with morphological noise. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 123–129.

Wenxiang Jiao, Xing Wang, Zhaopeng Tu, Shuming Shi, Michael Lyu, and Irwin King. 2021. Self-training sampling with monolingual data uncertainty for neural machine translation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2840–2850.

Tom Kocmi, Eleftherios Avramidis, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Markus Freitag, Thamme Gowda, Roman Grundkiewicz, Barry Haddow, Marzena Karpinska, Philipp Koehn, Benjamin Marie, Christof Monz, Kenton Murray, Masaaki Nagata, Martin Popel, Maja Popović, and 3 others. 2024. Findings of the WMT24 general machine translation shared task: The LLM era is here but MT is not solved yet. In *Proceedings of the Ninth Conference on Machine Translation*, pages 1–46.

Yongheng Li, Yahui Zhao, Guozhe Jin, Zhejun Jin, and Rongyi Cui. 2023. Local information fused transformer model for korean-chinese machine translation. In *2023 16th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, pages 1–6.

Clara Meister, Tim Vieira, and Ryan Cotterell. 2020. Best-first beam search. *Transactions of the Association for Computational Linguistics*, 8:795–809.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 48–53.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318.

Alberto Poncelas, Dimitar Shterionov, Andy Way, Gideon Maillette de Buy Wenniger, and Peyman Passban. 2018. Investigating backtranslation in neural machine translation. In *Proceedings of the 21st Annual Conference of the European Association for Machine Translation*, pages 269–278.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191.

Surangika Ranathunga, En-Shiun Annie Lee, Marjana Prifti Skenduli, Ravi Shekhar, Mehreen Alam, and Rishemjit Kaur. 2023. Neural machine translation for low-resource languages: A survey. *ACM Comput. Surv.*, 55.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Improving neural machine translation models with monolingual data. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 86–96.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725.

Aditya Siddhant, Ankur Bapna, Yuan Cao, Orhan Firat, Mia Chen, Sneha Kudugunta, Naveen Arivazhagan, and Yonghui Wu. 2020. Leveraging monolingual data with self-supervision for multilingual neural machine translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2827–2835.

Matthew Snover, Bonnie Dorr, Rich Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In *Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers*, pages 223–231.

Shuo Sun, Hongxu Hou, Nier Wu, Xin Chang, Xiaoning Jia, and Haoran Li. 2021. Iterative knowledge refinement-based dual learning for mongolian-chinese machine translation. *Journal of Xiamen University (Natural Science)*, 60(4):687–692.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Daimeng Wei, Zhanglin Wu, Hengchao Shang, Zongyao Li, Minghan Wang, Jiaxin Guo, Xiaoyu Chen, Zhengzhe Yu, and Hao Yang. 2023. Text style transfer back-translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7944–7959.

Xiangpeng Wei, Heng Yu, Yue Hu, Rongxiang Weng, Weihua Luo, and Rong Jin. 2022. Learning to generalize to more: Continuous semantic augmentation for neural machine translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7930–7944.

Xuerong Wei and Qing-Dao-Er-Ji Ren. 2024. A language-driven data augmentation method for mongolian-chinese neural machine translation. In *2024 International Conference on Asian Language Processing (IALP)*, pages 297–302.

Jiahao Xu, Yubin Ruan, Wei Bi, Guoping Huang, Shuming Shi, Lihui Chen, and Lemao Liu. 2022. On synthetic data for back translation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 419–430.

Ziyue Yan, Hongying Zan, Yifan Guo, and Hongfei Xu. 2024. Transferring zero-shot multilingual chinese-chinese translation model for chinese minority language translation. In *2024 International Conference on Asian Language Processing (IALP)*, pages 133–138.

Ziqing Yang, Zihang Xu, Yiming Cui, Baoxin Wang, Min Lin, Dayong Wu, and Zhigang Chen. 2022. CINO: A Chinese minority pre-trained language model. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 3937–3949.

Huinuan Zhang, Yatu Ji, Nier Wu, and Min Lu. 2024. A mongolianchinese neural machine translation method based on semantic-context data augmentation. *Applied Sciences*, 14(8).

Junjin Zhang, Yonghong Tian, Zheyu Song, and Yufeng Hao. 2023. Mongolian-chinese machine translation based on text context information. In *2023 8th International Conference on Intelligent Computing and Signal Processing (ICSP)*, pages 1741–1744.

Chao Zhaomuerlige and Sirigulun Wang. 2024. Chinese-mongolian bilingual legal domain question-answering corpus dataset. *China Scientific Data*, 9(04):83–91.

Chunting Zhou, Graham Neubig, and Jiatao Gu. 2019. Understanding knowledge distillation in non-autoregressive machine translation. *CoRR*, abs/1911.02727.