Cross-Preference Learning for Sentence-Level and Context-Aware Machine Translation

Anonymous ACL submission

Abstract

Context-aware machinne translation (MT) leverages document-level information, yet it does not consistently outperform sentence-level MT, as contextual signals are unevenly beneficial across sentences. Existing training objectives do not explicitly model this variability, limiting a model's ability to adaptively exploit context. In this paper, we propose Cross-Preference Learning (CPL), a preference-based training framework that explicitly captures the complementary benefits of sentence-level and context-aware MT. CPL achieves this by integrating both intra- and cross-condition preferences into the preference optimization objective. The introduction of intra- and cross-condition preferences provides explicit supervision on when and how contextual information improves translation quality. We validate the proposed approach on several public context-aware MT tasks using multiple models, including Qwen3-4B, Qwen3-8B, and LLaMA-3-8B. Experimental results demonstrate consistent improvements in translation quality and robustness across both input conditions, achieved without any architectural modifications. All data and code will be released.

1 Introduction

Modern machine translation (MT) systems are increasingly expected to operate under multiple input conditions. In some scenarios, only a single source sentence is available, while in others, additional inter-sentence context can be provided to improve translation quality (e.g., document-level or context-aware MT) (Tiedemann and Scherrer, 2017; Maruf et al., 2021). These two settings—sentence-level and context-aware translation—share the same output space but are typically handled by separate models and optimized independently.

A key observation underlying our work is that context-aware translation does not consistently outperform sentence-level translation. As illustrated in Figure 1, context-aware models greatly outperform sentence-level models for a subset of sentences, but also slightly underperform, or even greatly underperform for a non-negligible portion of the data, while performing on par in many cases. This distribution highlights that the two systems often produce diverse yet complementary translations rather than one uniformly dominating the other (Voita et al., 2018; Dong et al., 2025).[1] Consistent with this observation, Table 1 shows that the two systems achieve comparable overall BLEU and COMET scores, while the oracle results indicate substantial headroom when the better output is selected on a per-sentence basis. These findings motivate our approach: by explicitly comparing translations generated under different input conditions for the same source sentence, a model can learn to leverage context adaptively, preferring sentence-level translations when context is redundant or context-aware translations when additional context provides useful information.

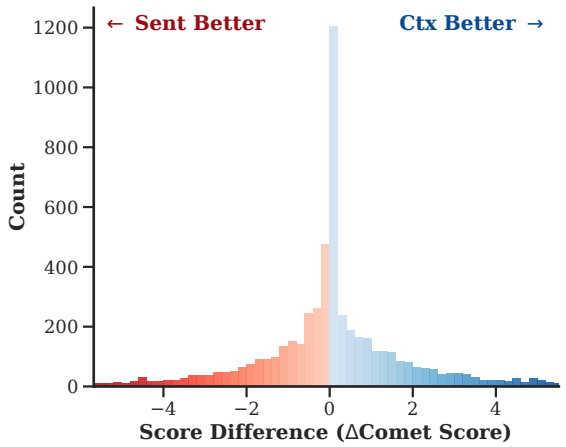

Figure 1: Distribution of COMET differences between sentence-level (Sent) and context-aware (Ctx) English–German translations produced by Qwen3-8B.

Inspired by recent advances in preference opti-

[1] Please refer to Section 4.1 for more details.

Model	BLEU	COMET
Sentence-level	31.72	86.12
Context-aware	31.60	86.13
Oracle	33.91	87.17

Table 1: Overall English-to-German translation quality of sentence-level and context-aware translation. *Oracle* means we always select the better translation from the two systems for each sentence.

mization, we cast the preference for using inter-sentence context in translation as a preference optimization problem, addressed via preference learning. However, existing methods such as direct preference optimization (DPO) (Rafailov et al., 2023), contrastive preference optimization (CPO) (Xu et al., 2024), and simplified preference optimization (SimPO) (Meng et al., 2024) focus on single-condition settings, where preference comparisons share the same input configuration. Consequently, these approaches are not designed to account for multiple input conditions sharing the same output space but differ in available information.

To address this limitation, we propose Cross-Preference Learning (CPL) built upon CPO. In addition to the intra-condition preference learning in vanilla CPO, CPL introduces a cross-condition preference optimization (Cross-CPO) to explicitly model the interactions between the two conditions. By ranking sentence-level and context-aware translations, CPL enables the model to learn a shared preference structure across conditions, allowing preference signals from one condition to influence learning in the other. Importantly, CPL operates entirely at the level of the training objective and requires no architectural changes, and can be applied to any shared-parameter translation system.

The main contributions in this paper can be summarized as follows:

- We extend preference-based optimization to jointly support sentence-level and context-aware translation, providing a principled framework for multi-task preference learning.
- We introduce CPL, which incorporates cross-condition preference comparisons to explicitly model interactions between the two translation conditions and adaptively leverage context.
- We evaluate CPL on multiple document-level MT tasks and show that a single trained model performs robustly under both sentence-level and context-aware settings, achieving significant improvements in translation quality and cross-condition consistency.

2 Methodology

Figure 2 provides an overview of Cross-Preference Learning (CPL). We first introduce the two translation settings in this work (Figure 2(a)) in Section 2.1, then describe our proposed CPL (Figure 2(b)) in Section 2.2.

2.1 Sentence- and Context-Conditioned Translation

We study a machine translation setting in which a single model operates under two source-side input conditions: sentence-level and context-aware translation. In the former, the model receives only a source sentence x, while in the latter it additionally receives source-side context c, such as neighboring sentences within a document.

The model, parameterized by θ, defines two conditional distributions over target sentences: $p_\theta(y \mid x)$ for sentence-level translation and $p_\theta(y \mid x, c)$ for context-aware translation. For each distribution, we sample two candidates: $\{y_{\mathrm{s}}^1, y_{\mathrm{s}}^2\}$ from $p_\theta(y \mid x)$ and $\{y_{\mathrm{c}}^1, y_{\mathrm{c}}^2\}$ from $p_\theta(y \mid x, c)$.

For each candidate pair, we construct preference labels based on automatic evaluation. Taking sentence-level translation as an example, we score each candidate using the average of sentence-level COMET and document-level COMET (d-COMET) (Vernikos et al., 2022) against the reference. The higher-scoring candidate is treated as the preferred translation y_{s}^+, while the lower-scoring one is treated as the dispreferred translation y_{s}^-. We apply the same procedure to the context-aware candidates to obtain the corresponding preference pair $(y_{\mathrm{c}}^+, y_{\mathrm{c}}^-)$.

Since translations produced under the two conditions are directly comparable, this setup enables preference modeling both within and across conditions. Our goal is to train a single model that performs robustly under both settings.

2.2 Cross-Preference Learning

Next, we first present the background for preference-based optimization in Section 2.2.1, followed by intra-condition preference learning (Section 2.2.2) and cross-condition preference learning (Section 2.2.3). Finally, we present overall CPL objective in Section 2.2.4.

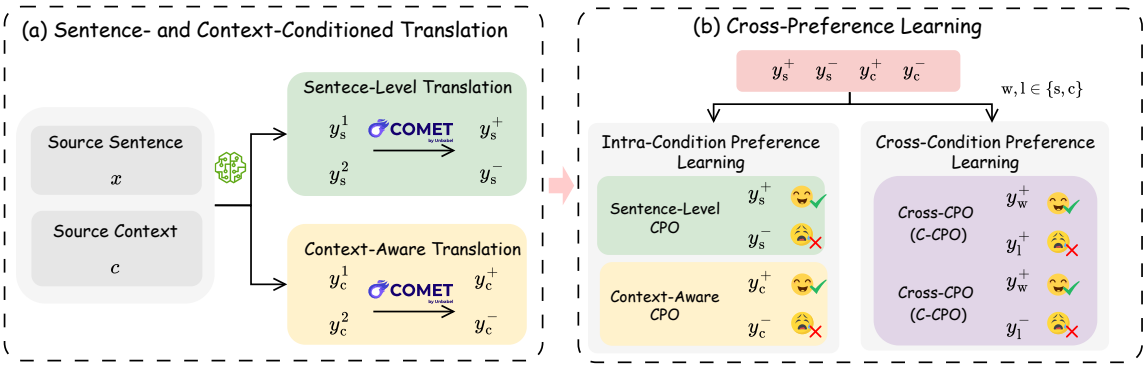

Figure 2: Illustration of our approach.

2.2.1 Preference-Based Optimization Background

Preference-based optimization trains models on pairwise comparisons of candidate translations rather than reference likelihood. For a preference pair (y^+, y^-) and input x, the model is encouraged to assign higher probability to y^+. When context is available, we treat x as (x, c) implicitly.

We adopt contrastive preference optimization (CPO) (Xu et al., 2024). The intra-condition CPO loss for a pair (y^+, y^-) is:

$$\mathcal{L}_{\text{CPO}}(x, y^+, y^-) = -\big[\log \sigma\big(\beta \log p_\theta(y^+ \mid x) - \beta \log p_\theta(y^- \mid x)\big)\big] - \log p_\theta\left(y^+ \mid x\right), \quad (1)$$

where σ is the sigmoid function, β controls preference separation.

2.2.2 Intra-Condition Preference Learning

We extend contrastive preference optimization (CPO), originally formulated for a single input condition, to the sentence- and context-conditioned translation. This extension enables preference-based optimization to be applied consistently across the two related tasks within a shared-parameter model.

CPO is applied independently to the selected preference pairs for each condition: (y_s^+, y_s^-) for sentence-level translation under $p_\theta(y \mid x)$, and (y_c^+, y_c^-) for context-aware translation under $p_\theta(y \mid x, c)$. Let $\mathcal{P}_s$ and $\mathcal{P}_c$ denote the selected sets of sentence-level and context-aware preference pairs, respectively. Intra-condition preference learning minimizes the following objective:

$$\mathcal{L}_{\text{intra}}(\theta) = \mathbb{E}_{(y^+,y^-)\sim\mathcal{P}_s}\left[\mathcal{L}_{\text{CPO}}\left(x, y^+, y^-\right)\right] + \mathbb{E}_{(y^+,y^-)\sim\mathcal{P}_c}\left[\mathcal{L}_{\text{CPO}}\left((x, c), y^+, y^-\right)\right], \quad (2)$$

where $\mathcal{L}_{\text{CPO}}$ is the CPO loss defined in Eq. 1, computed over sentence-level and context-aware preference pairs, respectively.

The intra-condition loss $\mathcal{L}_{\text{intra}}(\theta)$ enables effective preference-based learning within each translation condition while sharing model parameters across both tasks. Appendix A presents the details of preference pair selection for both $\mathcal{P}_s$ and $\mathcal{P}_c$.

2.2.3 Cross-Condition Preference Learning

Intra-condition preference learning optimizes sentence-level and context-aware translation independently, and therefore does not explicitly relate the two conditioned outputs. To exploit interactions across conditions, we introduce cross-condition preference learning, which directly compares sentence-level and context-aware translations for the same source sentence.

For each source sentence x with context c, we identify the best translation y_w^+ from four candidates, i.e., (y_s^+, y_s^-) and (y_c^+, y_c^-). The input condition that produces y_w^+ is defined as the winning condition (w), while the other serves as the losing condition (l), where $w, l \in \{s, c\}$. Then we construct two cross-condition preference pairs: (y_w^+, y_l^+) and (y_w^+, y_l^-). These pairs encourage the model to consistently prefer the winning-condition output over both strong and weak outputs from the losing condition. We denote the corresponding inputs as x_w^+, x_l^+, and x_l^-.

Let $\mathcal{P}_{\text{cr}}$ denote the set of cross-condition preference pairs. The cross-condition preference loss is defined as:

$$\begin{aligned}\mathcal{L}_{\text{cross}}(\theta) \quad (3)\\ =&\mathbb{E}_{(y_w^+,y_l^+)\sim\mathcal{P}_{\text{cr}}}\mathcal{L}_{\text{C-CPO}}\left(\{x_w^+, x_l^+\}, y_w^+, y_l^+\right)\\ +&\mathbb{E}_{(y_w^+,y_l^-)\sim\mathcal{P}_{\text{cr}}}\mathcal{L}_{\text{C-CPO}}\left(\{x_w^+, x_l^-\}, y_w^+, y_l^-\right).\end{aligned}$$

where the cross-CPO (C-CPO) loss is defined as:

$$\mathcal{L}_{\text{C-CPO}}(\{x^+, x^-\}, y^+, y^-) \quad (4)$$
$$= -\big[\log \sigma\big(\beta \log p_\theta(y^+ \mid x^+) - \beta \log p_\theta(y^- \mid x^-)\big)\big] - \log p_\theta(y^+ \mid x^+).$$

As shown, cross-CPO adapts the standard CPO objective to allow comparisons between translations generated under different conditioning signals while preserving the contrastive learning objective. Overall, the cross-condition loss $\mathcal{L}_{\text{cross}}(\theta)$ encourages the model to assign higher probability to preferred translations across input conditions, explicitly modeling interaction between sentence-level and context-aware outputs. Appendix A presents the details of preference pair selection for $\mathcal{P}_{\text{cr}}$.

2.2.4 CPL objective

CPL unifies intra- and cross-condition preference signals into a single objective, jointly optimizing sentence-level and context-aware translation under different input conditions.

The CPL objective is defined as the sum of the corresponding preference-based losses defined in Eq. 2 and Eq. 3:

$$\mathcal{L}_{\text{CPL}}(\theta) = \mathcal{L}_{\text{intra}}(\theta) + \mathcal{L}_{\text{cross}}(\theta). \quad (5)$$

By jointly optimizing intra-condition and cross-condition preference pairs, CPL enables a single shared-parameter model to perform robustly under both sentence-level and context-aware translation settings, without requiring architectural changes.

3 Experimentation

3.1 Experimental Settings

Datasets. Following recent work, we use the News Commentary v18.1 in WMT25,[2] which features parallel text with document boundaries. Our experiments cover six translation directions: from English (En) to German (De), Spanish (Es), French (Fr), Italian (It), Dutch (Nl), and Russian (Ru). Refer to Appendix B for more details of the datasets.

Similar to Xu et al. (2024), we constructed a small-scale dataset for the cold-start fine-tuning stage. For each direction, we extract a contiguous block of 20,000 sentences sequentially, ensuring the availability of context for context-aware training. Specifically, for the context-aware samples, we prepend the preceding source text, truncated to the last 256 tokens (Lyu et al., 2024), as the input context.

Following Xu et al. (2024) and Wang et al. (2025a), we use the high-quality validation sets to source the preference pairs. Appendix B shows the statistics of datasets used for CPL learning and the preference pairs used.

Models and Settings. We select Qwen3-4B[3] (Yang et al., 2025), Qwen3-8B[4] and Meta Llama-3-8B-Instruct[5] (AI@Meta, 2024) as the foundation open-source LLMs. For detailed fine-tuning and hyper-parameter settings, please refer to Appendix C.

Baselines. We compare our approach against the following baselines:

- **Sent-Level.** The base LLM translates each sentence independently. **Sent-Level$_{\text{tuned}}$** is fine-tuned on sentence-level data. Building on this model, we additionally apply CPO using sentence-level preference pairs, yielding **Sent-Level$_{\text{CPO}}$**.
- **Ctx-Aware.** The base LLM translates using the current sentence and its preceding context. **Ctx-Aware$_{\text{tuned}}$** is fine-tuned on context-aware data. Similarly, **Ctx-Aware$_{\text{CPO}}$** applies CPO with context-aware preference pairs.
- **Sent+Ctx$_{\text{tuned}}$.** A naive multi-condition baseline jointly fine-tuned on both sentence-level and context-aware data using standard likelihood training. **Sent+Ctx$_{\text{tuned+}}$** further incorporates the dataset used for extracting CPL preference pairs during fine-tuning.

All prompt details are provided in Appendix E.

Metrics. We primarily report *sentence-level COMET* scores (Rei et al., 2020). Specifically, we use the reference-based metric `wmt22-comet-da` (Rei et al., 2022a). In addition, we report supplementary evaluation metrics, including sentence-level BLEU (s-BLEU) (Post, 2018) and document-level COMET (d-COMET), in Appendix D. Since our model and most baselines support both input conditions, we evaluate and report performance for both sentence-level (*Sent*) and context-aware (*CTX*) translation.

[2] https://www2.statmt.org/wmt25/translation-task.html

[3] https://huggingface.co/Qwen/Qwen3-4B

[4] https://huggingface.co/Qwen/Qwen3-8B

[5] https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

#	Model	En ⇒ De		En ⇒ Es		En ⇒ Fr		En ⇒ It		En ⇒ Nl		En ⇒ Ru		*Average*	
		Sent	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*
							Qwen3-4B								
1	Sent-Level	82.51	-	84.91	-	83.13	-	86.94	-	82.71	-	83.12	-	83.89	-
2	Sent-Level$_{\text{tuned}}$	84.41	-	86.88	-	84.62	-	87.97	-	84.88	-	84.58	-	85.56	-
3	Sent-Level$_{\text{CPO}}$	85.14	-	87.43	-	85.18	-	88.66	-	85.88	-	86.19	-	86.41	-
4	Ctx-Aware	-	83.25	-	86.98	-	84.47	-	87.81	-	83.47	-	83.86	-	84.97
5	Ctx-Aware$_{\text{tuned}}$	-	84.31	-	86.85	-	84.64	-	88.01	-	84.85	-	84.86	-	85.59
6	Ctx-Aware$_{\text{CPO}}$	-	85.38	-	87.56	-	85.32	-	88.78	-	85.91	-	86.20	-	86.52
7	Sent+Ctx$_{\text{tuned}}$	84.66	84.79	87.07	87.02	84.60	84.61	88.18	88.27	85.16	85.08	85.04	84.95	85.79	85.79
8	Sent+Ctx$_{\text{tuned+}}$	84.58	84.60	87.11	87.12	84.74	84.78	88.39	88.39	85.31	85.32	84.88	84.83	85.84	85.84
9	CPL (Ours)	85.92	85.91	87.75	87.86	85.84	85.82	89.08	89.06	86.52	86.57	86.50	86.56	86.94	86.96
10	- IntraLoss	85.53	85.53	87.63	87.63	85.56	85.52	88.92	88.95	86.20	86.21	86.09	85.97	86.66	86.64
11	- CrossLoss	85.58	85.66	87.59	87.73	85.54	85.66	88.81	88.91	86.46	86.46	86.41	86.49	86.73	86.82
							Qwen3-8B								
1	Sent-Level	85.13	-	87.59	-	85.25	-	88.70	-	85.93	-	85.76	-	86.39	-
2	Sent-Level$_{\text{tuned}}$	86.12	-	87.73	-	85.82	-	89.12	-	87.07	-	86.34	-	87.03	-
3	Sent-Level$_{\text{CPO}}$	86.26	-	88.20	-	86.14	-	89.44	-	87.67	-	87.33	-	87.51	-
4	Ctx-Aware	-	85.05	-	87.72	-	85.35	-	88.75	-	86.09	-	85.59	-	86.43
5	Ctx-Aware$_{\text{tuned}}$	-	86.13	-	87.78	-	85.80	-	88.99	-	87.11	-	86.39	-	87.03
6	Ctx-Aware$_{\text{CPO}}$	-	86.54	-	88.29	-	86.26	-	89.47	-	87.60	-	87.32	-	87.58
7	Sent+Ctx$_{\text{tuned}}$	86.14	86.24	87.82	87.86	85.71	85.78	89.16	89.22	87.30	87.33	86.51	86.47	87.11	87.15
8	Sent+Ctx$_{\text{tuned+}}$	86.24	86.34	87.81	87.94	85.80	85.89	89.25	89.23	87.31	87.47	86.46	86.29	87.15	87.19
9	CPL (Ours)	87.19	87.23	88.47	88.51	86.56	86.63	89.81	89.99	88.22	88.28	87.71	87.75	87.99	88.06
10	- IntraLoss	86.85	86.85	88.34	88.35	86.38	86.34	89.68	89.67	87.86	87.83	87.41	87.26	87.75	87.72
11	- CrossLoss	86.88	87.00	88.33	88.39	86.39	86.54	89.74	89.74	87.97	87.99	87.35	87.43	87.78	87.85
							Llama-3-8B-Instruct								
1	Sent-Level	82.72	-	84.40	-	83.07	-	86.11	-	85.20	-	82.15	-	83.94	-
2	Sent-Level$_{\text{tuned}}$	86.00	-	87.59	-	85.44	-	88.99	-	88.22	-	85.82	-	87.01	-
3	Sent-Level$_{\text{CPO}}$	86.49	-	88.10	-	85.92	-	89.55	-	88.63	-	86.71	-	87.57	-
4	Ctx-Aware	-	51.33	-	56.62	-	50.41	-	58.05	-	53.51	-	53.05	-	53.83
5	Ctx-Aware$_{\text{tuned}}$	-	86.10	-	87.67	-	85.54	-	89.10	-	88.28	-	85.89	-	87.10
6	Ctx-Aware$_{\text{CPO}}$	-	86.72	-	88.15	-	86.19	-	89.56	-	88.69	-	86.77	-	87.68
7	Sent+Ctx$_{\text{tuned}}$	86.42	86.56	87.84	87.85	85.76	85.85	89.28	89.31	88.61	88.62	86.40	86.17	87.39	87.39
8	Sent+Ctx$_{\text{tuned+}}$	86.43	86.51	87.92	87.93	85.95	85.97	89.42	89.37	88.74	88.75	86.26	86.23	87.45	87.46
9	CPL (Ours)	87.09	87.19	88.43	88.45	86.60	86.65	89.82	89.85	88.93	89.00	87.42	87.43	88.05	88.10
10	- IntraLoss	87.00	87.03	88.29	88.32	86.44	86.47	89.69	89.77	88.79	88.79	87.16	86.94	87.90	87.89
11	- CrossLoss	86.98	87.11	88.17	88.16	86.41	86.42	89.69	89.71	88.94	88.95	87.35	87.39	87.92	87.96

Table 2: Results of different systems on COMET metric. Best scores are shown in dark red and second-best scores are in light red . *Sent* and *CTX* denote sentence-level and context-aware inputs, respectively.

3.2 Main Results

We begin with an important observation from Table 2. Across all models and training settings, sentence-level and context-aware translations (#2 vs. #5) achieve very similar COMET scores. This suggests that simply providing document-level context does not consistently improve average translation quality. Such behavior has also been observed in recent work, where the benefits of context are often sparse and localized (Dong et al., 2025; Lyu et al., 2024). This observation motivates our approach: rather than assuming context is always beneficial, we aim to adaptively learn when sentence-level or context-aware translation should be preferred. Based on the table, we further analyze the results as follows:

- **Effect of fine-tuning and joint training.** Among the baselines, fine-tuned LLMs consistently outperform their untuned counterparts (e.g., #2 vs. #1 and #5 vs. #4). Joint fine-tuning on both sentence- and context-conditioned data further improves performance for both tasks (#7 vs. #2 and #7 vs. #5). For example, with Llama-3-8B-Instruct, joint training yields average COMET gains of 0.38 and 0.29 over individually fine-tuned models, indicating that we establish a strong and competitive baseline.

- **Impact of incorporating additional training data.** Extending joint fine-tuning with the subset of data used for CPL (Sent+Ctx$_{\text{tuned+}}$, #8) leads to only marginal improvements, suggesting that performance gains are not simply driven by additional data, but require more effective learning signals. Moreover, using the additional training data for preference learning, both Sent-Level$_{\text{CPO}}$ (#3) and Context-Aware$_{\text{CPO}}$ (#6) achieve more improvement for both sentence-level and context-aware translation, respectively.

- **Effectiveness of CPL.** Compared with all baselines, CPL (#9) achieves substantial improvements. Notably, when compared to Sent+Ctx$_{\text{tuned+}}$ (#8), which leverages the same

training data, CPL yields consistent gains for both sentence-level and context-aware translation. For instance, CPL improves average COMET by 1.10/1.12, 0.84/0.87, and 0.60/0.64 for sentence-level/context-aware translation using Qwen3-4B, Qwen3-8B, and Llama-3-8B-Instruct, respectively. This demonstrates the effectiveness of Cross-Preference Learning beyond conventional fine-tuning. Moreover, CPL (#9) outperforms the two other strong baselines Sent-Level$_{\text{CPO}}$ (#3) and Context-Aware$_{\text{CPO}}$ (#6) which are augmented with preference learning on the same training data.

- **Ablation studies.** Ablation results (#9 vs. #10 vs. #11) show that both intra-condition loss and cross-condition loss contribute to CPL's performance. Removing either component degrades performance, with intra-condition loss having a slightly larger impact, indicating its complementary role in stabilizing preference learning.

- **Consistency across model scales.** Finally, the observed performance trends are consistent across all three LLM backbones, suggesting that CPL is robust and model-agnostic, and can be effectively applied to different pre-trained models.

4 Discussion

In this section, we use Qwen3-8B as the foundation model to discuss our approach. Unless otherwise specified, we report the average sentence-level COMET scores across all six translation tasks.

4.1 Distributional Analysis of Context Utility.

To better understand how Cross-Preference Learning affects the interaction between sentence-level and context-aware translation, we analyze the distribution of sentences for which one input condition substantially outperforms the other. Specifically, we categorize sentences into five groups based on the COMET score difference between the context-aware and sentence-level outputs, denoted as $\Delta = \text{COMET}_{\text{ctx}} - \text{COMET}_{\text{sent}}$. The categories are defined as follows: *clearly better* ($\Delta \geq 1.0$), *better* ($0.5 \leq \Delta < 1.0$), *on par* ($-0.5 < \Delta < 0.5$), *worse* ($-1.0 < \Delta \leq -0.5$), and *clearly worse* ($\Delta \leq -1.0$).

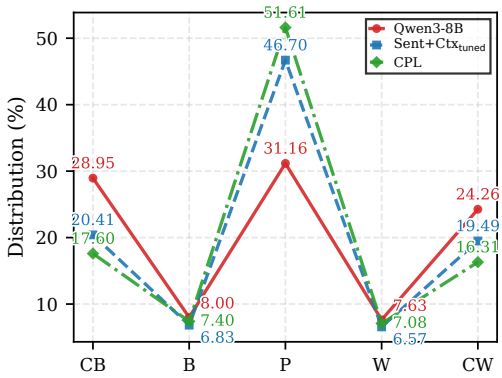

Figure 3: Distribution (%) of sentences by COMET differences between context-aware and sentence-level translations. CB/B/P/W/CW = *Clearly Better*, *Better*, *On Par*, *Worse*, *Clearly Worse*.

As shown in Figure 3, the untuned base model, Qwen3-8B, exhibits a large proportion of sentences in the *clearly better, CB* and *clearly worse, CW* categories, indicating that document context can substantially help some sentences while severely degrading others.

Joint fine-tuning (Sent+Ctx$_{\text{tuned}}$) mitigates this effect by increasing the proportion of *on par, P* cases, suggesting more balanced use of context. CPL further strengthens this trend, achieving the highest share of *on par, P* sentences while simultaneously reducing extreme improvements and degradations. Compared to the Qwen3-8B base model and Sent+Ctx$_{\text{tuned}}$, CPL produces more balanced and stable performance between sentence-level and context-aware translation, reducing extreme gains or degradations associated with context usage.

4.2 Leveraging Both Outputs via Reranking

An additional advantage of CPL is that it naturally supports both sentence-level and context-aware translation within a unified framework. Given a source sentence x and its context c, CPL produces two candidate translations: a sentence-conditioned output y and a context-conditioned output y'. Rather than committing to a single translation mode, these two candidates can be reranked, and the better one selected as the final output.

We report the results in Table 3. The first two rows show the standalone performance of CPL's sentence-level and context-aware outputs. We then evaluate three reranking strategies. *Prob.-based Reranking* selects the candidate with higher model likelihood, reflecting the model's internal confidence. *COMETKiwi-based Reranking* uses a

Model	BLEU	COMET
Sent-Level	36.61	87.99
Ctx-Aware	36.80	88.06
+ Prob.	37.14	88.19
+ COMETKiwi	37.13	88.42
+ Oracle	38.63	88.73

Table 3: Performance of reranking sentence-level and context-aware translations produced by CPL.

Metric Used	Sent	CTX
BLEU	86.96	87.16
d-COMET	87.97	87.98
s-COMET	87.97	88.03
(d- + s-COMET)/2	87.99	88.06

Table 4: CPL performance (in COMET) using different metrics for selecting intra- and cross-condition preference pairs.

reference-free quality estimator (Rei et al., 2022b), enabling automatic selection without gold references. *Oracle Reranking* selects the candidate with higher reference-based COMET score and serves as an upper bound. As shown, all reranking strategies consistently improve over individual outputs, demonstrating that sentence-level and context-aware translations provide complementary strengths. Prob.-based reranking yields modest gains, while KiwiCOMET achieves larger improvements, suggesting that semantic quality estimation is more effective than likelihood alone.

4.3 Effect of Preference Selection Metrics

Cross-Preference Learning relies on ranking candidate translations to construct informative intra-condition and cross-condition preference pairs. By default, we use the average of document-level COMET (d-COMET) and sentence-level COMET (s-COMET) as the selection metric. To assess the sensitivity of CPL to this design choice, we compare several alternatives, including d-COMET alone, s-COMET alone, and BLEU (Post, 2018).

Table 4 shows the performance. Among the COMET-based variants, performance differences are negligible, indicating that CPL is robust to different granularities of COMET scoring. In contrast, using BLEU as the selection metric leads to a noticeable performance drop. This is expected, as BLEU relies on surface-level n-gram overlap and is less aligned with semantic adequacy and discourse-level quality, which are crucial for selecting informative preference pairs.

Model	Coh. ↑	ALTI+ ↑	Fluency ↑
Qwen3-8B	73.28	54.49	3.81
Sent+Ctx$_{\text{tuned}}$	74.78	54.67	3.90
CPL (ours)	75.24	54.90	4.04

Table 5: Additional quality analysis using coherence (Coh.), ALTI+, and GPT-based fluency.

4.4 Analysis with Additional Quality Metrics

In addition to BLEU and COMET, we evaluate CPL using complementary metrics that target aspects of translation quality not fully captured by standard accuracy-based evaluation, namely discourse coherence, faithfulness, and fluency. These properties are particularly important for context-aware translation.

Following Li et al. (2023) and Dong et al. (2025), we measure discourse coherence (Coh.) by computing the cosine similarity between SimCSE sentence embeddings (Gao et al., 2021) of neighboring translated sentences. Higher scores indicate better consistency across sentence boundaries. To assess faithfulness, we report ALTI+ (Ferrando et al., 2022), which uses a pretrained NLLB model to detect under-translation and hallucination by analyzing attribution patterns during generation.[6] Higher ALTI+ scores correspond to fewer faithfulness issues. Finally, we follow Sun et al. (2025b) and evaluate translation fluency using GPT-5 (GPT-5-2025-08-07) (OpenAI, 2025) as an external judge , which provides a holistic assessment of grammaticality and naturalness.[7]

Table 5 reports results on complementary quality metrics. Sent+Ctx$_{\text{tuned}}$ improves coherence, faithfulness, and fluency over the base model, indicating more effective use of document context. CPL further achieves the best performance across all metrics, with higher discourse coherence, fewer faithfulness issues as measured by ALTI+, and improved fluency. These consistent gains suggest that CPL enhances translation quality beyond standard COMET evaluation.

4.5 Effect of Cross-Condition Decomposition

In cross-condition preference learning, we include two types of preference constraints: $(y_{\text{w}}^{+}, y_{\text{l}}^{+})$ and $(y_{\text{w}}^{+}, y_{\text{l}}^{-})$. To analyze their respective contributions,

[6] https://facebookresearch.github.io/stopes/docs/eval/alti

[7] Due to the high cost of API-based fluency evaluation (about $50 per direction), we report only the average scores for En⇒De and En⇒Ru.

Model	Sent	CTX
CPL	87.99	88.06
CPL w/o $(y_{\mathrm{w}}^{+}, y_{\mathrm{l}}^{+})$	87.98	88.01
CPL w/o $(y_{\mathrm{w}}^{+}, y_{\mathrm{l}}^{-})$	87.88	87.91

Table 6: Effect of removing individual cross-condition preference constraints.

we conduct an ablation study in which we remove one of the two preference pairs from the cross-condition loss.

As shown in Table 6, removing either constraint causes a small but consistent performance drop for both sentence-level and context-aware translation, indicating that both are beneficial. The degradation is slightly larger when removing $(y_{\mathrm{w}}^{+}, y_{\mathrm{l}}^{-})$, suggesting that contrasting against a weaker losing candidate provides a marginally stronger signal. These results suggest that the two cross-condition constraints play complementary roles and that CPL is not overly sensitive to any single preference relation. This redundancy contributes to the robustness of CPL, allowing CPL to maintain stable performance even when individual cross-condition signals are partially removed.

5 Related Work

LLM-based Document-level Machine Translation. With the emergence of LLMs, DocMT has been revisited by leveraging LLMs' strong contextual modeling and long-context capabilities. Early studies primarily evaluated prompt-based LLM performance on DocMT, analyzing how models such as ChatGPT handle extended source-side context (Wang et al., 2023; Karpinska and Iyyer, 2023). Subsequent work proposes more structured prompting and inference-time strategies, including retrieval-augmented generation (Cui et al., 2024), agent-based frameworks with memory mechanisms (Wang et al., 2025b; Guo et al., 2025), and iterative translation schemes that preserve discourse information across segments (Hu et al., 2025).

Another line of research focuses on supervised fine-tuning (SFT) to adapt LLMs explicitly for DMT. These methods explore instruction mixing (Li et al., 2024), multi-stage fine-tuning with monolingual and parallel documents (Wu et al., 2024a), sentence-level fine-tuning evaluated at the document level (Stap et al., 2024), and decoding- or prompt-enhanced training strategies (Lyu et al., 2024). Dong et al. (2025) refine translations by jointly leveraging intermediate outputs from sentence-level and document-level translation.

Different from above studies, in this work we explicitly address the interaction between sentence-level and context-aware translation outputs and provide mechanisms for selectively leveraging context.

Preference Learning for Machine Translation. Preference learning has long been explored in machine translation as an alternative to likelihood-based training (Hopkins and May, 2011; Cherry and Foster, 2012), using ranking-based or pairwise objectives to better align model outputs with human judgments. Recently, advances in LLM alignment, such as RLHF (Christiano et al., 2017), Direct Preference Optimization (DPO; Rafailov et al., 2023), and Contrastive Preference Optimization (CPO; Xu et al., 2024), have renewed interest in this paradigm. Several studies adapt these techniques to MT by constructing preference pairs from human annotations or automatic metrics, showing improvements in translation adequacy and fluency under a single input condition (Agrawal et al., 2024; Wu et al., 2024b; Yang et al., 2024; Cui et al., 2025; Sun et al., 2025a). In contrast to prior work, which applies preference learning within a single translation setting, our approach extends preference learning to a dual-condition scenario by explicitly modeling interactions between sentence-level and context-aware translation.

6 Conclusion

In this paper, we study sentence-level and context-aware machine translation from a unified perspective and show that, while their overall performance is often similar, their outputs exhibit substantial and systematic differences. Motivated by this observation, we propose Cross-Preference Learning (CPL), a preference-based optimization framework that jointly models intra-condition and cross-condition translation preferences, enabling a single model to leverage document context adaptively. Experiments across multiple document-level translation tasks demonstrate that CPL consistently improves both sentence-level and context-aware translation quality, enhances cross-condition consistency, and remains robust to context noise and metric choices. Our analysis further shows that CPL provides a simple yet effective way to align translation behavior across input conditions without architectural changes, offering a promising direction for robust and context-adaptive machine translation.

Limitations

While Cross-Preference Learning (CPL) shows consistent improvements for both sentence-level and context-aware translation, several limitations remain. First, CPL relies on high-quality preference pairs derived from automatic metrics (e.g., COMET), which may propagate metric biases and affect learning. Second, our approach requires sampling multiple candidates per sentence and computing their scores, which increases computational cost during training. Third, although CPL can leverage context selectively, its ability to handle extremely long documents or complex discourse phenomena has not been fully explored. Finally, our evaluations focus on a limited set of language pairs and LLM backbones; further studies are needed to validate CPL on broader languages and model scales.

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Task	Test		CPL	
	# Doc	# Sent	# Doc	# Sent
En ⇒ De	150	5,967	150	5,628
En ⇒ Es	150	5,819	150	5,782
En ⇒ Fr	150	5,795	150	5,890
En ⇒ It	150	5,749	150	5,948
En ⇒ Nl	151	5,992	151	5,925
En ⇒ Ru	150	5,619	150	5,691

Table 7: Statistics of test sets for the translation tasks.

Task	$\mathcal{P}_{\text{s}}$	$\mathcal{P}_{\text{c}}$	$\mathcal{P}_{\text{cr}}$
En ⇒ De	4,143	4,277	8,086
En ⇒ Es	4,963	5,051	8,736
En ⇒ Fr	4,768	4,877	8,829
En ⇒ It	4,923	5,024	8,877
En ⇒ Nl	3,904	4,072	8,056
En ⇒ Ru	4,016	4,116	7,841

Table 8: Statistics of preference pairs in cross-condition preference learning.

A Preference Pair Selection

We construct the sentence-level preference set $\mathcal{P}_{\text{s}}$ by filtering the preferred–dispreferred translation pairs $(y_{\text{s}}^{+}, y_{\text{s}}^{-})$ obtained in Section 2.1. A pair is retained only if it satisfies the following criteria: 1) both translations contain between 6 and 100 words; 2) both translations achieve quality scores higher than 0.3; and 3) the score margin between the two translations lies in the range $[0.2, 10]$.

These constraints filter out degenerate, low-quality, or weakly distinguishable pairs, ensuring that retained pairs provide reliable and informative preference signals. The same strategy is applied to construct the context-aware preference set $\mathcal{P}_{\text{c}}$.

Similarly, all preference pairs in the cross-preference set $\mathcal{P}_{\text{cr}}$ are required to satisfy the same selection criteria.

B Dataset

Table 7 shows the statistics of the test sets of six translation tasks, and the dataset used for CPL preference selection.

Table 8 shows the statistics of the preference datasets used in the six translation tasks. Specifically, in $\mathcal{P}_{\text{cr}}$, it shows the total number of preference pairs, including both types of cross-condition preference pairs, $(y_{\text{w}}^{+}, y_{\text{l}}^{+})$ and $(y_{\text{w}}^{+}, y_{\text{l}}^{-})$.

C SFT and CPL Settings

During SFT, we fine-tune the model using the LoRA approach. The LoRA rank is set to 16. The batch size is 256, and the learning rate is fixed at 5×10^{-5}. We train the model for a single epoch.

During CPL, we also adopt LoRA-based fine-tuning with the LoRA rank set to 16. The batch size is 128, and the learning rate is set to 5×10^{-5}. The model is trained for 2 epochs. The β parameter is set to 0.1, following Rafailov et al. (2023) and Xu et al. (2024).

D Experimental Results in s-BLEU and d-COMET

Table 9 shows the performance in document-level COMET (Vernikos et al., 2022) using the reference-based `wmt22-comet-da` (Rei et al., 2022a). Table 10 shows the performance in sentence-level SacreBLEU (Post, 2018).

E Prompts

In all experiments presented in this paper, we employ a unified set of prompt templates to ensure fair comparison.

As illustrated in Figure 4, the sentence-level template consists of a system instruction and the user input, where the source sentence is inserted into the `{src_sent}` placeholder. In contrast, as shown in Figure 5, following Wang et al. (2023), the context-aware template augments the input by introducing a `{context_text}` placeholder before the source sentence, explicitly instructing the model to incorporate inter-sentence context during translation.

#	Model	En ⇒ De		En ⇒ Es		En ⇒ Fr		En ⇒ It		En ⇒ Nl		En ⇒ Ru		*Average*	
		Sent	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*
							Qwen3-4B								
1	Sent-Level	79.00	-	81.29	-	79.50	-	83.26	-	79.35	-	79.23	-	80.27	-
2	Sent-Level$_{\text{tuned}}$	81.55	-	84.25	-	81.74	-	84.81	-	81.94	-	81.02	-	82.86	-
3	Sent-Level$_{\text{CPO}}$	82.40	-	84.90	-	82.37	-	85.57	-	82.98	-	82.73	-	83.49	-
4	Ctx-Aware	-	80.26	-	84.46	-	81.59	-	84.38	-	80.29	-	80.22	-	81.87
5	Ctx-Aware$_{\text{tuned}}$	-	81.52	-	84.26	-	81.84	-	84.85	-	81.95	-	81.38	-	82.88
6	Ctx-Aware$_{\text{CPO}}$	-	82.74	-	85.03	-	82.60	-	85.74	-	83.15	-	82.83	-	83.68
7	Sent+Ctx$_{\text{tuned}}$	81.78	82.00	84.44	84.46	81.70	81.83	85.04	85.20	82.24	82.20	81.53	81.43	83.04	83.14
8	Sent+Ctx$_{\text{tuned+}}$	81.72	81.85	84.49	84.55	81.87	81.96	85.29	85.37	82.43	82.53	81.31	81.26	82.85	82.92
9	CPL (Ours)	83.23	83.25	85.22	85.38	83.02	83.08	86.00	86.04	83.82	83.84	83.01	83.09	84.26	84.32
10	- IntraLoss	82.82	82.83	85.10	85.11	82.76	82.78	85.81	85.91	83.39	83.48	82.64	82.53	83.98	84.02
11	- CrossLoss	82.86	83.02	85.07	85.24	82.76	82.95	85.76	85.93	83.67	83.72	82.92	83.01	84.02	84.17
							Qwen3-8B								
1	Sent-Level	82.15	-	85.01	-	82.38	-	85.51	-	83.08	-	82.04	-	83.36	-
2	Sent-Level$_{\text{tuned}}$	83.37	-	85.17	-	82.99	-	86.06	-	84.37	-	82.88	-	84.14	-
3	Sent-Level$_{\text{CPO}}$	83.65	-	85.69	-	83.41	-	86.44	-	85.07	-	83.91	-	84.69	-
4	Ctx-Aware	-	82.29	-	85.15	-	82.59	-	85.56	-	83.40	-	81.99	-	83.50
5	Ctx-Aware$_{\text{tuned}}$	-	83.43	-	85.25	-	83.04	-	86.00	-	84.48	-	82.97	-	84.20
6	Ctx-Aware$_{\text{CPO}}$	-	83.95	-	85.79	-	83.56	-	86.53	-	85.03	-	83.97	-	84.81
7	Sent+Ctx$_{\text{tuned}}$	83.39	83.58	85.27	85.35	82.89	83.03	86.15	86.23	84.69	84.74	83.03	82.97	84.24	84.32
8	Sent+Ctx$_{\text{tuned+}}$	83.49	83.68	85.24	85.41	82.98	83.13	86.25	86.25	84.72	84.91	82.90	82.71	84.26	84.35
9	CPL (Ours)	84.63	84.69	86.00	86.05	83.82	83.92	86.78	87.05	85.69	85.84	84.32	84.36	85.21	85.32
10	- IntraLoss	84.23	84.32	85.85	85.88	83.64	83.64	86.69	86.69	85.32	85.33	83.98	83.87	84.95	84.95
11	- CrossLoss	84.29	84.44	85.83	85.91	83.68	83.85	86.84	86.81	85.42	85.45	83.98	84.02	85.01	85.08
							Llama-3-8B-Instruct								
1	Sent-Level	78.32	-	80.56	-	79.22	-	81.46	-	81.20	-	77.15	-	79.65	-
2	Sent-Level$_{\text{tuned}}$	83.26	-	85.07	-	82.54	-	85.93	-	85.63	-	82.21	-	84.11	-
3	Sent-Level$_{\text{CPO}}$	83.86	-	85.63	-	83.15	-	86.58	-	86.12	-	83.27	-	84.77	-
4	Ctx-Aware	-	44.93	-	50.38	-	44.08	-	51.81	-	46.62	-	45.98	-	47.30
5	Ctx-Aware$_{\text{tuned}}$	-	83.39	-	85.20	-	82.80	-	86.02	-	85.73	-	82.34	-	84.25
6	Ctx-Aware$_{\text{CPO}}$	-	84.14	-	85.67	-	83.47	-	86.61	-	86.20	-	83.38	-	84.91
7	Sent+Ctx$_{\text{tuned}}$	83.69	83.84	85.34	85.38	82.95	83.05	86.29	86.29	86.14	86.20	82.77	82.64	84.53	84.57
8	Sent+Ctx$_{\text{tuned+}}$	83.67	83.81	85.39	85.43	83.12	83.20	86.42	86.36	86.30	86.34	82.70	82.73	84.60	84.65
9	CPL (Ours)	84.44	84.59	85.98	86.04	83.84	83.95	86.83	86.89	86.49	86.58	83.99	83.99	85.26	85.34
10	- IntraLoss	84.41	84.45	85.79	85.84	83.62	83.76	86.63	86.76	86.34	86.37	83.65	83.54	85.07	85.12
11	- CrossLoss	84.42	84.56	85.65	85.71	83.69	83.75	86.68	86.73	86.48	86.55	83.89	83.98	85.14	85.21

Table 9: Results of different systems on document-level COMET metric. Best scores are shown in dark red and second-best scores are in light red . *Sent* and *CTX* denote sentence-level and context-aware inputs, respectively.

Prompt Template

Translate the text enclosed in triple quotes from `{src_lang}` into `{tgt_lang}` without any explanation.

`{src_lang}`: ''' `{src_sent}` '''

Figure 4: Prompt used for Sentence-level translation (Sent-Level).

Prompt Template

[`{src_lang}`]:`{context_text}`

Given the provided context, translate the following `{src_lang}` sentence to `{tgt_lang}`.

[`{src_lang}`]:`{src_sent}`

Figure 5: Prompt used for Context-Aware translation (Ctx-Aware).

#	Model	En ⇒ De		En ⇒ Es		En ⇒ Fr		En ⇒ It		En ⇒ Nl		En ⇒ Ru		*Average*	
		Sent	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*	*Sent*	*CTX*
							Qwen3-4B								
1	Sent-Level	12.64	-	28.95	-	22.16	-	22.75	-	14.78	-	14.38	-	19.28	-
2	Sent-Level$_{\text{tuned}}$	24.92	-	40.05	-	31.94	-	35.38	-	24.38	-	22.20	-	31.33	-
3	Sent-Level$_{\text{CPO}}$	28.99	-	41.73	-	35.16	-	36.25	-	28.61	-	26.49	-	32.87	-
4	Ctx-Aware	-	11.09	-	28.98	-	21.21	-	21.35	-	12.72	-	13.05	-	18.07
5	Ctx-Aware$_{\text{tuned}}$	-	26.73	-	40.02	-	32.79	-	35.20	-	24.46	-	23.26	-	31.84
6	Ctx-Aware$_{\text{CPO}}$	-	27.71	-	41.29	-	34.94	-	35.14	-	30.30	-	24.99	-	32.40
7	Sent+Ctx$_{\text{tuned}}$	28.11	28.95	41.33	39.42	33.54	33.38	36.65	36.56	27.51	28.32	24.89	25.52	33.43	33.33
8	Sent+Ctx$_{\text{tuned+}}$	28.42	29.15	41.47	40.74	32.84	33.46	37.26	37.52	29.74	28.17	24.79	25.19	32.42	32.37
9	CPL (Ours)	29.38	29.46	42.03	41.99	35.50	35.63	35.87	35.32	33.16	33.24	27.38	27.39	35.19	35.13
10	- IntraLoss	29.10	30.03	41.64	41.75	35.11	35.27	36.00	36.69	32.71	32.80	26.30	27.18	34.91	35.31
11	- CrossLoss	30.56	29.98	41.87	41.87	34.89	34.97	36.37	36.01	32.91	32.21	26.78	26.80	35.32	35.01
							Qwen3-8B								
1	Sent-Level	16.95	-	35.96	-	25.91	-	27.32	-	18.39	-	18.41	-	23.82	-
2	Sent-Level$_{\text{tuned}}$	31.72	-	42.65	-	35.48	-	38.59	-	34.66	-	28.66	-	35.29	-
3	Sent-Level$_{\text{CPO}}$	33.47	-	43.79	-	37.40	-	38.90	-	35.01	-	30.12	-	36.45	-
4	Ctx-Aware	-	14.44	-	31.60	-	23.43	-	24.58	-	16.16	-	14.78	-	20.83
5	Ctx-Aware$_{\text{tuned}}$	-	31.60	-	42.55	-	35.44	-	38.44	-	34.14	-	28.61	-	35.13
6	Ctx-Aware$_{\text{CPO}}$	-	33.34	-	43.38	-	37.07	-	39.05	-	34.29	-	30.12	-	36.21
7	Sent+Ctx$_{\text{tuned}}$	31.91	31.88	43.57	43.62	36.06	35.96	39.77	39.62	35.58	35.75	29.19	28.83	36.01	35.94
8	Sent+Ctx$_{\text{tuned+}}$	32.38	32.42	43.65	43.86	36.22	36.12	40.34	40.42	34.87	36.39	29.14	28.72	36.10	36.32
9	CPL (Ours)	32.28	33.26	44.22	44.24	37.80	37.78	38.80	39.73	36.51	35.75	30.03	30.06	36.61	36.80
10	- IntraLoss	33.79	33.83	43.93	44.12	37.54	37.73	39.16	39.50	36.47	34.94	30.32	30.35	36.87	36.74
11	- CrossLoss	33.70	33.82	44.01	44.13	37.11	37.33	39.57	39.44	36.47	35.86	29.85	30.24	36.79	36.80
							Llama-3-8B-Instruct								
1	Sent-Level	26.29	-	35.30	-	31.16	-	31.59	-	30.37	-	24.33	-	29.84	-
2	Sent-Level$_{\text{tuned}}$	31.80	-	42.96	-	35.10	-	38.97	-	38.31	-	27.93	-	35.85	-
3	Sent-Level$_{\text{CPO}}$	33.34	-	44.15	-	37.51	-	39.93	-	38.47	-	29.39	-	37.13	-
4	Ctx-Aware	-	13.33	-	18.12	-	15.80	-	16.27	-	13.98	-	13.27	-	15.13
5	Ctx-Aware$_{\text{tuned}}$	-	32.11	-	43.20	-	35.32	-	39.26	-	38.50	-	28.14	-	36.09
6	Ctx-Aware$_{\text{CPO}}$	-	33.49	-	44.13	-	37.67	-	39.42	-	38.46	-	29.55	-	37.12
7	Sent+Ctx$_{\text{tuned}}$	32.96	33.15	44.40	44.34	36.27	36.55	40.33	40.37	40.13	40.29	28.74	28.65	37.14	37.23
8	Sent+Ctx$_{\text{tuned+}}$	32.94	33.32	44.36	44.48	36.59	36.58	40.67	40.82	40.55	40.59	28.91	28.75	37.34	37.42
9	CPL (Ours)	33.87	33.95	44.17	44.37	37.82	38.09	39.86	40.09	39.23	39.14	29.93	29.73	37.48	37.56
10	- IntraLoss	33.70	34.17	44.18	44.47	37.14	37.93	39.40	39.62	39.16	39.09	29.87	30.04	37.24	37.55
11	- CrossLoss	32.90	33.75	44.09	44.05	37.24	37.43	39.44	39.52	39.09	39.01	29.48	29.34	37.04	37.18

Table 10: Results of different systems on sentence-level BLEU metric. Best scores are shown in dark red and second-best scores are in light red. *Sent* and *CTX* denote sentence-level and context-aware inputs, respectively.