Domain Translation with Monolingual Lexical Distribution

Anonymous authors
Paper under double-blind review

Abstract

Neural machine translation (NMT) often demands a large amount of high-quality training data when adapting to a new domain with a carefully designed fine-tuning strategy. However, constructing a sufficient amount of parallel data for training poses challenges even for fine-tuning. This work proposes to fine-tune a generic NMT model using only the monolingual lexical distribution estimated from a small amount of in-domain data in the target language. Word frequency plays a critical role in analyzing the differences among corpora in various fields, e.g., psycholinguistic and language education, and our challenge lies in whether we can fit a model using the naive statistics collected from a target language domain in NMT. We leverage a variant of energy-based models (EBMs) based on Conditional Distributional Policy Gradients (CDPG) with a large number of EBMs to constrain the fine-tuning process with lexical distribution. We conduct experiments across four translation directions and four domain datasets, totaling 16 domain adaptation scenarios. The results demonstrate that our method enables robust domain shift while mitigating catastrophic forgetting, achieving effective domain adaptation using only a small amount of monolingual resources.

1 Introduction

Thanks to the crawling technology and corpora construction efforts (Tiedemann, 2012; Bañón et al., 2020; Morishita et al., 2022), we have access to abundant parallel translation data, resulting in the development of high-performance pre-trained neural machine translation (NMT) models. However, NMT models suffer from performance degradation when translating text from the domains different from the domain of the training corpus due to the mismatch of the domain-specific terminologies (Koehn & Knowles, 2017; Shen et al., 2021; Pang et al., 2025). While general-purpose parallel translation data is abundantly available, automatically collecting a sufficient amount of domain-specific parallel data is challenging, and such special-purpose translation tends to require custom-made parallel data due to its specialized environment, e.g., terminologies in the medical domain or textual styles for a specific company, demanding a specialist to construct or check the quality of the parallel data (Chu & Wang, 2018; Yeganova et al., 2021).

In this study, we leverage easily accessible pre-trained NMT models and propose to adapt a general domain NMT model to a specific domain by using only the monolingual lexical distribution obtained from monolingual domain data in the target language. Lexical distribution, or word frequency, is crucial in analyzing the differences of corpora (Kilgarriff, 1997; Rayson & Garside, 2000), and the simple statistics have been investigated in various fields, such as psycholinguistic (Garlock et al., 2001) and language learning (Laufer & Nation, 1995), to quantify language usages. Our challenge lies in whether we can adapt a model to a new domain using the naive statistics, i.e., monolingual lexical distribution, which are already employed in various language assessments and easily estimated from the specific domain in the target language without consulting a specialist to translate or check the bilingual data qualities.

However, naively performing fine-tuning of a pre-trained NMT model and forcibly changing its token prediction distribution can lead to catastrophic forgetting issues, ranging from the loss of fluency (Korbak et al., 2022; Choshen et al., 2020; Kiegeland & Kreutzer, 2021) to degradation in non-specific domains (Saunders & DeNeefe, 2024; Gu & Feng, 2020; Thompson et al., 2019), thereby causing a reduction in translation performance. To achieve the domain shift while reducing catastrophic forgetting, i.e., harmlessly modifying the model's knowledge without degradation in generalization performance or excessive overfit to a spe-

cific domain, we represent the lexical distribution of the target domain as conditional energy-based models (EBMs) and approximate the EBMs using Conditional Distributional Policy Gradients (CDPG) (Korbak et al., 2022), which is a variant of the Generation under Distributional Control (GDC) framework (Khalifa et al., 2021). Korbak et al. (2022) had only verified the effectiveness of CDPG for small shifts, such as translating numeral nouns (e.g., "two") as digits (e.g., "2"), while our method employs sparse features, i.e., the monolingual lexical distribution of the target domain by treating each token-level statistic as a feature, enabling domain shifts in a fine-grained manner without catastrophic forgetting.

We confirm its effectiveness across several domain adaptation benchmarks (Tian et al., 2014; Koehn & Knowles, 2017; Aharoni & Goldberg, 2020) and scenarios, covering four language directions and four domain datasets, resulting in a total of 16 settings, thus we achieved unsupervised domain adaptation using only target-side domain data. Moreover, we propose Dynamic CDPG, which dynamically adjusts parameters using a small amount of bilingual validation data (or back-translated data in a fully unsupervised setting) to search for better configurations and analyze ideal settings for unsupervised domain adaptation. Our analysis of CDPG and Dynamic CDPG reveals that while selecting parameters sensitively can sometimes yield the best results, a simple CDPG can sufficiently achieve domain shift while reducing catastrophic forgetting.

2 Conditional Distributional Policy Gradients

Conditional Distributional Policy Gradients (CDPG) (Korbak et al., 2022) approximates the generative probabilities of a language model to a target distribution while preventing catastrophic forgetting. It softly modifies the pre-trained parameters θ by shifting its generation distribution slightly by EBMs through fine-tuning.

We define the pre-trained conditional language model $a(\boldsymbol{x}|\boldsymbol{c})$ where $\boldsymbol{c}$ is a context, i.e., an input source language sentence, and $\boldsymbol{x}$ is a sentence, i.e., in a target language, sampled from the entire distribution $\mathcal{X}$ given $\boldsymbol{c}$. We introduce an energy-based model (EBM) $p_{\boldsymbol{c}}(\boldsymbol{x})$ as a controlled language model defined as:

$$p_{\boldsymbol{c}}(\boldsymbol{x}) = \frac{1}{Z_{\boldsymbol{c}}} a(\boldsymbol{x}|\boldsymbol{c}) b(\boldsymbol{x}, \boldsymbol{c}). \tag{1}$$

Here, $Z_{\boldsymbol{c}} = \sum_{\boldsymbol{x} \in \mathcal{X}} a(\boldsymbol{x}|\boldsymbol{c}) b(\boldsymbol{x}, \boldsymbol{c})$ is a partition function that normalizes the entire EBM $p_{\boldsymbol{c}}(\boldsymbol{x})$, and $b(\boldsymbol{x}, \boldsymbol{c})$ is a control condition function which is 1 when a certain constraint is met. When $b(\boldsymbol{x}, \boldsymbol{c})$ is reduced to a product of binary scorers $\phi_i(\boldsymbol{x}) \in \{0, 1\}$ as proposed by Khalifa et al. (2021), the EBM is formulated as:

$$p_{\boldsymbol{c}}^{point}(\boldsymbol{x}) = \frac{1}{Z_{\boldsymbol{c}}^{point}} a(\boldsymbol{x}|\boldsymbol{c}) \prod_i \phi_i(\boldsymbol{x}). \tag{2}$$

However, with binary constraints, only two values can be handled: either always meeting a specific condition or not, making it impossible to address needs such as satisfying a constraint with a probability of 0.5. For example, if we tackle to reduce the bias in the text generation style considering gender, the desired constraint is 0.5 for female characters and 0.5 for male characters. Khalifa et al. (2021) proposed a distributional constraint method for unconditional EBM $p(\boldsymbol{x}) = \frac{1}{Z} a(\boldsymbol{x}) b(\boldsymbol{x})$ to resolve the problem, and Kruszewski et al. (2023) adapt it to the conditional EBM with exponential family as follows:

$$p_{\boldsymbol{c}}^{dist}(\boldsymbol{x}|\boldsymbol{\lambda}) = \frac{1}{Z_{\boldsymbol{c}}^{dist}} a(\boldsymbol{x}|\boldsymbol{c}) \exp(\boldsymbol{\lambda} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \boldsymbol{c})), \tag{3}$$

where $\boldsymbol{\lambda}$ is a parameter vector of the distribution features. The parameter $\boldsymbol{\lambda}$ is determined through fine-tuning by starting from random initialization and iteratively updated by stochastic gradient descent (SGD) to minimize the loss function considering a distribution over contexts $\tau(\boldsymbol{c})$ as follows:

$$\nabla_{\boldsymbol{\lambda}} \mathcal{L}_{coef}(\boldsymbol{\lambda}) = \mathbb{E}_{\boldsymbol{c} \sim \tau(\boldsymbol{c})} \mathbb{E}_{\boldsymbol{x} \sim p_{\boldsymbol{c}}^{dist}(\cdot;\boldsymbol{\lambda})} \boldsymbol{\phi}(\boldsymbol{x}, \boldsymbol{c}) - \bar{\boldsymbol{\mu}}, \tag{4}$$

where $\bar{\boldsymbol{\mu}}$ is the probability for each feature and the moments $\mathbb{E}_{\boldsymbol{x} \sim p_{\boldsymbol{c}}^{dist}(\cdot;\boldsymbol{\lambda})}$ are computed through self-normalized importance sampling using $a(\cdot)$. In the previous example, if female characters are expected, the probability becomes 0.5.

However, since the EBM $p_{\boldsymbol{c}}(\boldsymbol{x})$ in Equation 1 that satisfies these constraints is not an autoregressive language model, it cannot perform generation. Therefore, training is conducted using the autoregressive model $\pi_\theta(\boldsymbol{x}|\boldsymbol{c})$ to approximate p on average across contexts by minimizing the expected cross-entropy loss CE$(\cdot)$ between $\pi_\theta(\boldsymbol{x}|\boldsymbol{c})$ and multiple $p_{\boldsymbol{c}}$ of the EBM as follows:

$$\mathcal{L}(\theta) = \mathbb{E}_{\boldsymbol{c}\sim\tau(\boldsymbol{c})} \operatorname{CE}\left(p_{\boldsymbol{c}}^{dist}(\cdot), \pi_\theta(\cdot \mid \boldsymbol{c})\right). \tag{5}$$

The gradient of this objective takes the following form:

$$\nabla_\theta \mathcal{L}(\theta) = \mathbb{E}_{\boldsymbol{c}\sim\tau(\boldsymbol{c})} \nabla_\theta \operatorname{CE}\left(p_{\boldsymbol{c}}^{dist}(\cdot), \pi_\theta(\cdot \mid \boldsymbol{c})\right) \tag{6}$$

$$= -\mathbb{E}_{\boldsymbol{c}\sim\tau(\boldsymbol{c})} \mathbb{E}_{\boldsymbol{x}\sim p_{\boldsymbol{c}}^{dist}(\boldsymbol{x})} \nabla_\theta \log \pi_\theta(\boldsymbol{x} \mid \boldsymbol{c}) \tag{7}$$

$$= -\mathbb{E}_{\boldsymbol{c}\sim\tau(\boldsymbol{c})} \mathbb{E}_{\boldsymbol{x}\sim\pi_\theta(\boldsymbol{x}|\boldsymbol{c})} \frac{p_{\boldsymbol{c}}^{dist}(\boldsymbol{x})}{\pi_\theta(\boldsymbol{x} \mid \boldsymbol{c})} \nabla_\theta \log \pi_\theta(\boldsymbol{x} \mid \boldsymbol{c}). \tag{8}$$

The loss function is used by importance sampling from π_θ. By iteratively training these for θ, π_θ can approximate the generative probability of the target EBM, enabling autoregressive generation. Details defer to Korbak et al. (2022). Note that the CDPG is a method for fine-tuning a model; thus, it does not introduce any changes to parameter size, model architecture, or inference speed.

3 Domain Adaptation by CDPG

3.1 Adaptation to Monolingual Lexical Distribution

We leverage monolingual data in the specific domain in the target language, e.g., English reports in the medical domain, and propose domain adaptation for NMT with CDPG using only the subword frequency information as features. When applying CDPG for NMT, the source sentence corresponds to a context $\boldsymbol{c}$, and the ideal target sentence is derived from $p_{\boldsymbol{c}}^{dist}(\boldsymbol{x}|\boldsymbol{\lambda})$. For training CDPG under distribution constraints in Equation 3, it requires a binary scorer $\phi_i(\boldsymbol{x}, \boldsymbol{c})$ and a parameter λ_i for each feature.

Under this setting, we employ $\boldsymbol{\phi}(\boldsymbol{x}, \boldsymbol{c})$ as features whether each subword of the target domain is included in $\boldsymbol{x}$. Moreover, when learning the parameter vector $\boldsymbol{\lambda}$ in Equation 4, we set the probability of each constraint, $\bar{\boldsymbol{\mu}}$, as the ratio of the frequency of subwords in the whole text in the target domain as follows:

$$\bar{\mu_i} = \frac{Freq^{target}(x_i)}{\sum_{x_j \in X} Freq^{target}(x_j)}, \tag{9}$$

where $Freq^{target}$ denotes the frequency of each subword x_i in the target text in the vocabulary X. By performing the above operations, we attempt to address the domain shift by utilizing the frequency of all subwords of the target domain text. Since this feature selection only uses data from the target side, the creation of the EBM model only requires the target side domain text.

3.2 Dynamic CDPG

EBM is iteratively updated by Equation 4 to approximate the generative language model toward the expected probability distribution for the target domain. The procedure involves generating multiple sentences $\boldsymbol{x}$ with context $\boldsymbol{c}$ through nucleus sampling (Holtzman et al., 2020), and the parameter of nucleus sampling, top-p, controls the diversity of generated outputs, where a lower value of top-p means the generated sentences are closer to the target distribution. However, there exists a large gap between the distribution of the pre-trained model and the target distribution, meaning that CDPG requires different top-p settings for different domain, e.g., higher top-p for larger gap in distance. Furthermore, the rate at which the model is fitting toward the target distribution in CDPG is not constant, demanding higher value of top-p for the larger distance, but lower value for the closer one. Therefore, we introduce Dynamic CDPG, which dynamically adjusts top-p in each iteration of the approximation to the EBM in Equation 1, searching for better configuration of CDPG.

A bilingual development set[1] is leveraged in Dynamic CDPG to guide the training process by measuring the current progress on the dataset. The basic idea of Dynamic CDPG is to divide the training process into

[1]The development set refers to the text used to generate features.

several iterations, then start with a constant parameter for top-p, and reconsider it in each training iteration such that a smaller top-p will be selected in the next iteration if a larger top-p leads to inferior performance on the development set. Note that if synthetic bilingual data can be obtained via back-translation from the target in-domain data, the setting can still be regarded as fully unsupervised. For each iteration, we use an evaluation method, such as BLEU (Papineni et al., 2002), to assess the model's performance and decide whether to accept that iteration. Specifically, we heuristically define two potential value sets for top-p, $\mathbb{A} = [0.5, 0.4, 0.3, 0.2, 0.1]$ in descending order and $\mathbb{B} = [0.6, 0.7, 0.8, 0.9, 1.0]$ in ascending order, where $\mathbb{A}$ enables the model to gradually fit with the target features, while $\mathbb{B}$ implies gradually conservative behavior in learning by sampling diverse tokens. We start the iteration with the first element of $\mathbb{A}$ as the value of top-p; if this iteration is accepted, we proceed to the next iteration with the second element of $\mathbb{A}$; if rejected, we switch to $\mathbb{B}$ and continue iterating until all elements in either $\mathbb{A}$ or $\mathbb{B}$ are completely iterated. Our preliminary studies showed that the training under Dynamic CDPG is always stable under our top-p scheduling.

4 Experimental Setup

4.1 Datasets

We conduct experiments with four translation pairs of English to German (`en`→`de`), German to English (`de`→`en`), English to Chinese (`en`→`zh`), and Chinese to English (`zh`→`en`). For pairs involving `de`, we collect four domains, including IT, Medical, Law, and Koran from the public corpus[2] released by Koehn & Knowles (2017); Aharoni & Goldberg (2020), where each domain has 2,000 sentences for the development set and test set, respectively[3]. For pairs involving `zh`, we collect four domains, including Education, Laws, Thesis, and Science, from the UM-Corpus (Tian et al., 2014), which is public[4] with high quality. Although this corpus provides 456 − 790 sentences for test sets in those 4 domains, the development set is not provided. Therefore, we randomly select 3,000 sentences from the training data for each domain as the development sets. Moreover, we use the development sets[5] of WMT from 2018 − 2022 (Bojar et al., 2018; Barrault et al., 2019; 2020; Akhbardeh et al., 2021; Kocmi et al., 2022), i.e., 14,482 translation instances of the newsdev set from a news domain, to train CDPG for all translation directions by treating them as a generic domain data set. Specifically, the contexts $\tau(\boldsymbol{c})$ are collected from the 14,482 source language sentences of the newsdev set, and the domain features $\bar{\boldsymbol{\mu}}$ are derived from the target language sentences of the domain-specific instances.

4.2 Models

Baselines We employ four open-source NMT models (Tiedemann & Thottingal, 2020) from HuggingFace Transformers[6] (Wolf et al., 2020) as backbones in our experiments, denoted as Pre-trained. These models are based on the Transformer architecture (Vaswani et al., 2017) and are trained on OPUS (Tiedemann, 2012) with the same configuration[7] comprising the 6 encoder and decoder layers, 8 attention heads, embedding size of 512, and an inner size of 2048. Since CDPG fine-tunes all parameters, we first establish a baseline by naively fine-tuning the model on the development sets, denoted as Fine-tuned. We also adopt LoRA (Hu et al., 2022) as a second baseline, which adapts attention weights with an inner rank of 8. The baseline is then fine-tuned using the same setup as Fine-tuned, offering robustness and reduced susceptibility to catastrophic forgetting when working with smaller datasets (Xu et al., 2023; Biderman et al., 2024). We set the batch size to 128 and the learning rate to 2e-7 for both settings. As another baseline, we conduct back-translation (Sennrich et al., 2016), denoted as Back-trans. Specifically, we generate source-language data using a reverse-direction model and the same target-language data used for fine-tuning. The model is

[2] `https://github.com/roeeaharoni/unsupervised-domain-clusters`

[3] Given the low quality of this corpus, we clean it and re-align the test set using `de` as the basis to avoid potential bias in evaluation. The low quality includes but is not limited to repetition, no alignment, and noise. Furthermore, the refined test data is completely unseen, enabling evaluation without any data contamination issues in the existing training corpus (Raunak & Menezes, 2022). We will make the cleaned dataset publicly available for future studies.

[4] `http://nlp2ct.cis.umac.mo/um-corpus/`

[5] `http://data.statmt.org/wmt23/general-task/dev.tgz`

[6] `https://huggingface.co/Helsinki-NLP`

[7] Details in: `https://huggingface.co/Helsinki-NLP/opus-mt-en-zh/blob/main/config.json`

then fine-tuned on the generated data using the same settings. All fine-tuning experiments are conducted for 10 epochs. The checkpoint achieving the best performance on the development set is selected as baselines.

CDPG For training the parameter vector $\boldsymbol{\lambda}$ in Equation 4, we set a batch size of 8 and a learning rate of 0.05 with a constant learning rate scheduler based on the training loss in our preliminary studies. Likewise, for fine-tuning CDPG model parameters θ in Equation 5, we set batch size of 128, epochs of 10, and learning rate of 2e-5 with a constant learning rate scheduler and Adam optimizer (Kingma & Ba, 2017). We always set top-p to 0.5 in training $\boldsymbol{\lambda}$ and fine-tuning θ. Moreover, we set the character length of the considered features, i.e., subwords, to be no less than 3 to filter insignificant features, and the input texts are pre-processed by the tokenizer in each pre-trained model. We used *disco* (Kruszewski et al., 2023) to implement the CDPG.

Dynamic CDPG We maintain the hyperparameters of CDPG for Dynamic CDPG. Dynamic CDPG is additionally supervised using the bilingual development set to dynamically select the best top-p value at each iteration, as described in Section 3.2. We create synthetic bilingual data by back-translation, similar to Back-trans. Therefore, Dynamic CDPG can still be regarded as fully unsupervised in the same manner as CDPG. In our preliminary experiment comparing back-translated bilingual data and the actual bilingual development set, the tuning results were the same. One possible reason is that the target-side lexical distribution plays a more important role than the source-side or full parallel data. Thus, we use back-translated data for Dynamic CDPG while maintaining the unsupervised setting. We set each iteration of Dynamic CDPG to 10 epochs. We use BLEU (Papineni et al., 2002) to calculate the validation score for each epoch. Additionally, we set a threshold that requires at least three improvements in the validation score for an iteration to be accepted. The initial learning rate of each subsequent iteration is set by dividing that of the previously accepted iteration by the square root of the number of epochs, to ensure training stability.

4.3 Evaluation

We set the beam size of 4 for each model to generate translations for the entire test set, and did not employ nucleus sampling (Holtzman et al., 2020) in the final evaluation for consistent evaluation in all settings. Then, translations are evaluated by four automatic MT evaluation methods: 1) Confidence (Müller et al., 2019; Wang et al., 2020), calculated as the average of the Softmax probabilities assigned to each generated token by the NMT system. 2) BLEU (Papineni et al., 2002), assessed with the implementation of SacreBLEU (Post, 2018) to measure the surface-level similarities, 3) NIST (Doddington, 2002), which is similar to BLEU but gives special attention to low-frequency words to assess the qualities of domain-specific terminologies, and 4) BERTScore (Zhang et al., 2020), which reports embedding similarities by Precision, Recall, and F1 scores, where the F1 score being the harmonic mean of Precision and Recall.

5 Experimental Results

Table 1 shows the experimental results for `en`→`de` and `de`→`en` translation pairs, and Table 2 shows the results for `en`→`zh` and `zh`→`en` translation pairs.

Finding 1: Naive supervised fine-tuning methods (almost) fail at domain adaptation with limited in-domain data. First, compared to Pre-trained, both Fine-tuned and LoRA, which naively utilize supervision signals from parallel in-domain sentences, generally fail to achieve improvements, except for slight gains in *Medical* of `en`→`de`, *Laws* of `en`→`zh`, and *Thesis* and *Science* of `zh`→`en`. Furthermore, Back-trans, which synthesizes pseudo-parallel data for fine-tuning, often performs comparably or worse than Fine-tuned, which uses a small amount of curated in-domain data. These results indicate that in limited-resource settings, such as domain adaptation, naive adaptation from a pure NMT model, such as Pre-trained, not only fails to improve performance but often leads to degradation.

Finding 2: CDPG improves confidences and performances on low-frequency, domain-specific terms. Next, compared to Pre-trained, although CDPG consistently improves Confidence, its performance in BLEU and BERTScore varies across domains. Specifically, in domains such as *IT* of `en`↔`de` and *Education* of `en`↔`zh`, where other baseline methods show only limited gains, CDPG achieves improvements

Table 1: Our main evaluation results for the en→de and de→en translation pairs. Pre-trained indicates the performance of the original models without any fine-tuning, while the other methods are described in Section 4.2. Conf. is the abbreviation of Confidence, and P and R represent the Precision and Recall scores of BERTScore, respectively. The best score in each block, which is divided by domain and language pair, is highlighted in **bold**. The checkmark (✓) indicates that parallel in-domain sentences were used as supervision signals. Identical scores between Dynamic CDPG and CDPG, such as Koran domain in de→en, indicate that Dynamic CDPG rejected all updates after initialization. Red cells indicate improvements from the base model Pre-trained to the CDPG-based model.

Domain		Method	en→de						de→en					
			Conf.	BLEU	NIST	P	R	F1	Conf.	BLEU	NIST	P	R	F1
IT		Pre-trained	68.39	27.58	5.97	87.48	87.70	87.52	72.02	38.80	7.96	94.93	94.92	94.91
	✓	Fine-tuned	67.91	27.92	6.04	87.38	87.60	87.42	71.76	38.83	7.95	94.94	94.93	94.92
	✓	LoRA	67.79	26.88	5.83	87.33	87.56	87.37	71.46	38.32	7.86	94.92	94.91	94.91
		Back-trans	67.90	27.89	6.01	87.38	87.59	87.41	71.49	38.35	7.86	94.93	94.92	94.91
		CDPG	74.44	29.01	6.25	87.68	87.77	87.67	**77.91**	39.79	8.30	94.95	94.94	94.93
		Dynamic CDPG	**79.36**	**30.78**	**6.58**	**88.00**	**87.87**	**87.89**	77.65	**40.55**	**8.34**	**95.01**	**94.96**	**94.98**
Medical		Pre-trained	75.93	43.19	8.45	91.55	91.17	91.31	78.06	**45.50**	8.47	**96.65**	**96.50**	**96.57**
	✓	Fine-tuned	75.71	43.23	8.46	91.53	91.14	91.29	77.77	45.48	8.47	96.64	**96.50**	96.56
	✓	LoRA	75.50	**43.56**	8.52	91.55	91.15	91.30	77.72	44.31	8.35	96.61	96.49	96.54
		Back-trans	75.50	43.56	8.52	91.57	91.17	91.32	77.65	45.47	8.55	96.64	96.49	96.56
		CDPG	80.85	42.54	**8.60**	**91.61**	**91.28**	**91.40**	**82.84**	44.56	**8.56**	96.57	**96.50**	96.53
		Dynamic CDPG	**82.32**	43.51	8.54	91.60	91.20	91.36	**82.84**	44.56	**8.56**	96.57	**96.50**	96.53
Law		Pre-trained	72.49	44.82	9.01	89.38	89.11	89.22	72.89	**51.75**	10.05	96.06	**95.75**	**95.90**
	✓	Fine-tuned	72.08	44.83	9.01	89.39	89.10	89.22	72.53	51.70	10.04	96.06	95.74	95.89
	✓	LoRA	72.05	44.80	9.01	**89.42**	89.12	**89.25**	72.55	51.67	10.04	96.05	95.73	95.89
		Back-trans	72.05	44.62	8.97	89.39	89.10	89.22	72.45	51.69	10.05	96.06	95.74	95.89
		CDPG	77.36	44.12	**9.05**	89.33	**89.17**	89.22	**78.12**	51.61	10.12	96.02	95.72	95.86
		Dynamic CDPG	**78.18**	**44.87**	9.03	89.40	89.09	89.22	73.02	51.64	**10.15**	**96.07**	95.73	95.89
Koran		Pre-trained	61.51	**18.90**	5.25	81.59	**80.18**	80.84	59.23	20.86	5.66	**91.95**	91.07	**91.49**
	✓	Fine-tuned	61.39	18.86	5.24	81.56	80.16	80.82	58.80	20.81	5.65	91.94	91.06	91.48
	✓	LoRA	61.18	18.86	5.24	81.54	80.13	80.80	58.94	20.83	5.65	91.94	91.05	91.48
		Back-trans	61.15	18.84	5.24	81.53	80.13	80.79	58.78	20.79	5.65	91.94	91.06	91.49
		CDPG	**67.00**	18.40	**5.26**	81.46	80.06	80.72	**64.75**	**20.94**	**5.67**	91.90	**91.09**	91.48
		Dynamic CDPG	61.30	18.85	5.25	**81.63**	80.16	**80.85**	**64.75**	**20.94**	**5.67**	91.90	**91.09**	91.48

across all metrics. In contrast, in domains like *Law* and *Koran* of en↔de, *Medical* of de→en, and *Laws* of en→zh, the improvements in BLEU and BERTScore are limited. However, NIST scores, which place greater emphasis on low-frequency words, still improve in all cases. This indicates that the consistent increases in Confidence and NIST scores are due to improved handling of domain-specific terms, which are often struggle to capture in general MT evaluation metrics such as BLEU because of their relatively low frequency. Therefore, compared to the baselines, domain adaptation using CDPG is shown to be more robust, even in the settings where access to parallel in-domain data is limited or unavailable.

Finding 3: While Dynamic CDPG often provides slight improvements, CDPG with fixed parameters already demonstrates sufficient performance. Dynamic CDPG aims to improve MT metrics, such as BLEU, by dynamically controlling and selecting parameters based on evaluations using a small amount of parallel in-domain development data at each epoch. Since BLEU is used as the guiding signal, Dynamic CDPG consistently achieves higher BLEU scores than CDPG. In domains such as *IT* of en↔de, *Thesis* of en→zh, and *Education* of zh→en, Dynamic CDPG selects parameters that further boost the improvements already observed in CDPG. Moreover, Dynamic CDPG mitigates the performance degradation seen with CDPG in some domains, including *Medical*, *Law*, and *Koran* of en→de, and *Science* of zh→en. Table 3 summarizes the top-p values selected and how they changed during training. In *Medical* and *Koran* of de→en and *Laws* of en→zh, the selected top-p remained identical to the default CDPG setting,

Table 2: Our main evaluation results for the en→zh and zh→en translation pairs. Notation and other corresponding information are the same as in Table 1.

Domain		Method	en→zh						zh→en					
			Conf.	BLEU	NIST	P	R	F1	Conf.	BLEU	NIST	P	R	F1
Education		Pre-trained	49.88	30.26	0.73	83.82	82.18	82.94	60.15	23.49	5.56	94.44	94.16	94.30
	✓	Fine-tuned	49.28	30.07	0.68	83.70	81.96	82.78	59.63	23.54	5.56	94.43	94.16	94.29
	✓	LoRA	49.03	30.19	0.68	83.70	81.92	82.75	59.64	23.69	5.57	94.49	94.16	94.30
		Back-trans	49.13	30.04	0.67	83.69	81.91	82.74	59.65	23.48	5.56	94.44	94.15	94.29
		CDPG	**57.88**	31.03	0.93	84.59	**83.23**	**83.86**	66.05	23.69	5.60	94.52	**94.28**	94.40
		Dynamic CDPG	57.22	**31.16**	**0.94**	**84.71**	83.01	83.81	**67.02**	**24.23**	**5.67**	**94.60**	**94.28**	**94.44**
Laws		Pre-trained	62.06	51.73	0.59	89.67	**89.70**	89.65	63.84	32.36	6.11	94.55	93.52	94.02
	✓	Fine-tuned	61.46	51.71	0.59	89.74	**89.70**	**89.69**	63.47	32.27	6.10	94.52	93.49	93.99
	✓	LoRA	61.38	**51.87**	0.60	**89.75**	89.63	89.66	63.16	32.33	6.09	94.51	93.45	93.97
		Back-trans	61.26	51.61	0.56	89.75	89.69	89.69	63.18	32.22	6.07	94.52	93.46	93.97
		CDPG	**68.50**	50.81	**0.68**	89.60	89.65	89.60	69.68	34.54	6.34	94.68	93.77	94.21
		Dynamic CDPG	**68.50**	50.81	**0.68**	89.60	89.65	89.60	**70.50**	**35.06**	**6.38**	**94.74**	**93.87**	**94.29**
Thesis		Pre-trained	47.62	18.95	1.14	76.09	75.69	75.78	50.83	8.65	3.48	89.55	88.33	88.92
	✓	Fine-tuned	47.23	19.94	1.39	76.42	**75.75**	75.99	50.11	8.60	3.46	89.56	88.31	88.91
	✓	LoRA	47.22	19.34	1.25	76.36	75.72	75.93	50.15	**8.71**	3.48	89.58	88.33	88.93
		Back-trans	46.98	19.95	1.36	76.40	75.70	75.95	50.05	8.67	3.47	89.58	88.30	88.92
		CDPG	**54.19**	19.94	1.29	76.11	75.53	75.72	57.16	8.49	3.51	89.52	88.38	88.93
		Dynamic CDPG	51.22	**20.14**	**1.52**	**76.53**	75.72	**76.03**	**58.57**	8.53	**3.54**	**89.67**	**88.37**	**89.00**
Science		Pre-trained	47.56	24.45	0.94	81.28	79.06	80.09	57.97	16.20	4.86	92.80	92.60	92.69
	✓	Fine-tuned	47.00	24.52	0.94	81.26	79.05	80.07	57.48	**16.36**	**4.88**	**92.82**	92.60	**92.70**
	✓	LoRA	46.75	24.57	0.96	81.38	79.09	80.15	57.49	16.29	**4.88**	92.81	92.60	**92.70**
		Back-trans	46.77	24.46	0.93	81.26	79.07	80.08	57.48	16.33	4.87	92.81	92.60	**92.70**
		CDPG	**56.27**	24.78	**1.02**	81.48	**79.70**	**80.53**	64.06	15.96	**4.88**	92.76	**92.66**	**92.70**
		Dynamic CDPG	52.38	**24.80**	1.00	**81.63**	79.39	80.43	**65.55**	16.34	4.86	92.79	92.60	92.69

Table 3: The top-p values used in Dynamic CDPG. Values are presented in the order they are used.

	IT	Medical	Law	Koran
en→de	0.5,0.4,0.8	0.5,0.7,1.0	0.5,0.8	1.0
de→en	0.5,0.9	0.5	0.5,0.9	0.5

	Education	Laws	Thesis	Science
en→zh	0.5,0.9	0.5	0.5,0.7	0.5,0.6,0.7
zh→en	0.5,0.4	0.5,0.4	0.5,0.6,0.7,0.8	0.5,0.3,0.2,0.1

resulting in the same scores reported in Tables 1 and 2. These findings suggest that while Dynamic CDPG can yield further improvements under metric supervision, the fixed-parameter CDPG already delivers strong and stable results. Therefore, although parameter tuning is ideal, CDPG is not overly sensitive to the top-p value, and a fixed value of 0.5 is generally sufficient.

6 Discussion

6.1 When Is CDPG Effective?

Based on the results in Tables 1 and 2, and the discussion in Section 5, although CDPG-based methods consistently improved Confidence and NIST, performance fluctuations were observed depending on each domain. To better understand under what conditions CDPG is effective, we conduct a detailed analysis focusing on the distributional differences between the pre-trained models and the monolingual lexical distribution features of CDPG described in Section 3.1.

First, we extract the term frequency-based features $\bar{\boldsymbol{\mu}}$ from the development set (***Dev Features***) and the test set (***Test Features***). Next, we generate translations for the development set using the pre-trained model and extract features from these translations (***Pretrained Features***). Using these three types of features,

Table 4: Comparisons of the target-side lexical distribution features. The prefix *len.* indicates the number of features, and *sim.* denotes the cosine similarity (in percent). *len.1* and *len.2* refer to the lengths of the first and second feature sets in each comparison. *itr* and *uni* indicate that the similarity was computed over the intersection or the union of the two sets, respectively.

		Case (i): *Dev Features* v.s. *Pretrained Features*						Case (ii): *Dev Features* v.s. *Test Features*					
Pair	Domain	len.1	len.2	len.itr	**sim.itr**	len.uni	**sim.uni**	len.1	len.2	len.itr	**sim.itr**	len.uni	**sim.uni**
en→de	IT	5,832	5,553	4,152	83.14	7,233	65.09	5,832	5,475	3,366	93.14	7,941	90.99
en→de	Koran	4,543	3,948	2,931	95.69	5,560	95.48	4,543	4,435	3,300	98.81	5,678	98.67
de→en	Law	7,054	6,469	5,668	98.80	7,855	98.66	7,054	7,014	4,754	98.19	9,314	97.91
de→en	Medical	6,543	6,130	5,367	95.83	7,306	94.97	6,543	6,577	4,604	94.22	8,516	93.48
en→zh	Thesis	7,533	7,518	5,395	74.88	9,656	73.23	7,533	3,755	3,188	92.81	8,100	91.82
en→zh	Laws	6,903	6,783	4,865	68.11	8,821	64.99	6,903	1,852	1,373	29.43	7,382	24.64
zh→en	Education	10,680	9,546	7,379	80.64	12,847	79.92	10,680	2,357	1,885	70.37	10,711	65.13
zh→en	Science	9,807	9,127	6,866	61.38	12,068	60.64	9,807	3,089	2,317	65.39	11,692	56.79

Table 5: Results of CDPG with fixed top-p values of 0.5, 0.8, and 1.0. The results for top-$p = 0.5$ are the same as those reported in Tables 1 and 2, and the abbreviations are consistent with those tables. The best score in each row is highlighted in **bold**. The row order aligns with Table 4.

		top-$p = 0.5$				top-$p = 0.8$				top-$p = 1.0$			
Pair	Domain	Conf.	BLEU	NIST	F1	Conf.	BLEU	NIST	F1	Conf.	BLEU	NIST	F1
en→de	IT	74.44	29.01	6.25	**87.67**	**74.67**	**29.13**	**6.28**	87.66	67.87	28.19	6.08	87.47
en→de	Koran	67.00	18.40	5.25	80.72	**67.14**	18.50	5.29	80.74	61.30	**18.85**	**5.35**	**80.85**
de→en	Law	78.12	**51.61**	10.12	95.86	**78.33**	51.53	**10.16**	95.86	71.83	51.58	**10.16**	**95.87**
de→en	Medical	82.84	44.56	8.56	96.53	**83.06**	44.82	**8.61**	**96.54**	77.72	**45.06**	**8.61**	**96.54**
en→zh	Thesis	**54.19**	19.94	1.29	75.72	53.93	**19.98**	**1.48**	**75.86**	46.96	19.95	1.47	75.76
en→zh	Laws	68.50	50.81	**0.68**	89.60	**68.78**	51.16	0.65	89.63	61.68	**51.90**	0.61	**89.71**
zh→en	Education	**66.05**	23.69	5.60	**94.40**	65.86	**23.92**	**5.65**	94.37	59.68	23.50	5.58	94.31
zh→en	Science	**64.06**	15.96	**4.88**	**92.70**	63.93	16.14	4.87	**92.70**	57.29	**16.34**	**4.88**	92.69

we compute the cosine similarity between two feature sets in the following two cases. **Case (i)** compares *Dev Features* and *Pretrained Features* to examine how much CDPG can improve over PRE-TRAINED. **Case (ii)** compares *Dev Features* and *Test Features* to indicate how uniformly the lexical distributions are aligned across the sampled sets. To account for differences in feature set lengths, which arise from zero counts due to mismatches in word usage, we compute similarity using both the *intersection* and the *union* of the sets.

Table 4 presents the analysis of features to complement Tables 1, 2 in some representative domains. Focusing on *IT* of en→de, we observe that in Case (i), the similarity *sim.uni* is low (65.09), suggesting that the pre-trained model does not perform well on this domain. Consequently, CDPG successfully improves overall performance by aligning features more closely with those of the *IT* domain. Similar trends are also observed in the *Thesis* domain of en→zh and the *Education* domain of zh→en. In contrast, in the *Koran* domain, the similarity is already high (95.69), so the impact of CDPG is limited. A similar trend is observed in de→en. Turning to *Laws* of en→zh and *Science* of zh→en, although the similarity in Case (i) is relatively low, CDPG-based methods show only limited improvement. Looking at Case (ii), the similarity *sim.uni* is also quite low, indicating that the lexical distribution is scattered. In such cases, simply approximating the feature space is insufficient to improve BLEU or other metrics, as the issue lies in a distribution mismatch within the same domain data. However, even in these scenarios, both NIST and Confidence scores consistently improve, suggesting that CDPG still succeeds in generating domain-specific terms. In summary, CDPG is most effective when there exists a relatively large gap in feature distribution in the pre-trained model, indicating that it can achieve faithful domain shifts under such conditions.

Table 6: Translation examples from the outputs of PRE-TRAINED and CDPG. We select one short and one long sentence for each of `en`→`de` and `en`→`zh`. In #Changes, the numerator indicates the number of sentences in which CDPG made changes compared to PRE-TRAINED, and the denominator indicates the size of the test set. Words highlighted in red indicate correct domain-specific usage, those in blue represent updated terms that do not match the correct target term, and underlined words indicate inaccurate translations.

Domain: IT	Pair: `en`→`de`	#Changes: 662/2000
Input	SubDialog has one state, default.	
Reference	SubDialog hat nur einen Status, Standard.	
PRE-TRAINED	SubDialog hat einen Zustand, default.	
CDPG	SubDialog hat einen Zustand, Standard.	
Domain: Medical	**Pair: `en`→`de`**	**#Changes: 748/2000**
Input	4 ml of solution in a 5 ml vial (type I glass) closed with a latex-free stopper (bromobutyl/ isoprene polymer) and a seal (lacquered plastic).	
Reference	4 ml Lösung in einer 5 ml-Durchstechflasche (Glastyp I), die mit einem latexfreien Stopfen (Bromobutyl/Isoprenpolymer) und eine Kappe (lackierter Kunststoff) verschlossen ist.	
PRE-TRAINED	4 ml Lösung in einer 5-ml-Durchstechflasche (Glas Typ I), die mit einem latexfreien Stopfen (Brombutyl/Isoprenpolymer) und einem Siegel (Lackkunststoff) verschlossen ist.	
CDPG	4 ml Lösung in einer 5 ml Durchstechflasche (Glas Typ I), die mit einem latexfreien Stopfen (Brombutyl/Isoprenpolymer) und einem Siegel (lackierter Kunststoff) verschlossen ist.	
Domain: Education	**Pair: `en`→`zh`**	**#Changes: 408/790**
Input	What an absurd suggestion!	
Reference	多荒谬的建议啊！	
PRE-TRAINED	胡说八道！	
CDPG	多么荒谬的建议！	
Domain: Thesis	**Pair: `en`→`zh`**	**#Changes: 414/625**
Input	Newton's transformation family f w(z)=z-1wz w-1 containing only one complex parameter w(w≠0 or 1) is constructed from the transcendental mapping z→e z w+c.	
Reference	用超越复映射F(z) =ezw+c构造出含有单参数w(w≠ 0或1)的牛顿变换族fw(z) =z- 1wzw-1模型，fw(z)有可数无穷多个极值点。	
PRE-TRAINED	牛顿的变换型fw(z) =z-1wz W-1 仅包含一个复合参数w(w)0 或1) 的f(z) =z-1wz W-1。	
CDPG	牛顿的变换型fw(z) =z-1wz W-1 仅包含一个复合参数w(w)0 或1)，是用超常绘图ze z+c 构造的w-1模型。	

Finally, to evaluate the sensitivity of CDPG to parameter settings, we fix the top-p value at three levels: 0.5, 0.8, and 1.0. Table 5 shows the resulting score variations. Based on these results and the analysis in Table 4, we categorize the outcomes into two scenarios. First, when the similarity between *Dev Features* and *Pretrained Features* (Case i) is low and the similarity between *Dev Features* and *Test Features* (Case ii) is high, smaller top-p values tend to yield better performance. This pattern is observed in domains such as *Thesis* of `en`→`zh` and *IT* of `en`→`de`. In contrast, using top-$p = 1.0$ helps maintain performance in domains like *Laws* of `en`→`zh` and *Science* of `zh`→`en`. Second, when the similarity between *Dev Features* and *Pretrained Features* (Case i) is already high, the performance improvement from CDPG is generally limited. In such cases, score variation across different top-p values is small, and top-$p = 1.0$ tends to be the safest choice. In addition, we observe that the Confidence score consistently changes with the top-p value, regardless of the actual translation quality. These results support our earlier discussion that the performance of CDPG is influenced by the properties of the provided monolingual lexical distribution features, such as the gap between the pre-trained model and the target domain, as well as the consistency of domain distributions.

6.2 Qualitative Analysis

Table 6 presents four representative translation instances that illustrate subtle effects of CDPG not fully captured by quantitative metrics. We first observe that CDPG only partially modifies the original model's knowledge, as demonstrated by conservative changes in the translations, and primarily enhances the model's term choice. Specifically, for the two `en`→`de` instances, regardless of sentence length, only domain-specific terms are modified without affecting the overall semantics or syntax, resulting in conservative behavior where not all test set inferences are altered. These findings confirm our motivation that CDPG can modify

Table 7: Relative differences between the scores of Fine-tuned and Dynamic CDPG. The columns and rows indicate the domains used for training and testing, respectively. Underlined values denote aligned cases where the training and testing domains are the same. *Gen.f.t.* and *Gen.d.c.* indicate the differences between Pre-trained and Fine-tuned, and between Pre-trained and Dynamic CDPG, respectively, on a generic domain (newstest2020). These serve as pivots for measuring relative differences.

		Confidence					BLEU				
		Education	Thesis	Science	Gen.f.t.	Gen.d.c.	Education	Thesis	Science	Gen.f.t.	Gen.d.c.
	Education	7.94	8.29	9.21	-1.16	8.52	1.09	0.29	-0.44	-0.76	-0.17
→zh	Thesis	6.70	3.99	5.58	-0.31	7.69	0.87	0.20	0.37	-0.28	0.13
	Science	4.83	4.20	5.38	-0.68	4.92	0.87	0.50	0.28	-0.02	0.33
	Education	7.39	7.86	7.83	-0.59	8.31	0.69	-0.07	-0.27	-0.11	0.19
→en	Thesis	7.72	8.46	8.03	-0.51	8.84	0.66	-0.11	0.09	-0.04	0.20
	Science	7.81	8.51	8.07	-0.55	8.89	0.64	-0.26	-0.02	-0.07	0.26
		IT	Medical	Koran	Gen.f.t	Gen.d.c.	IT	Medical	Koran	Gen.f.t	Gen.d.c.
	IT	10.61	8.97	9.90	-0.22	12.75	2.86	0.38	-1.13	-0.15	-1.65
→de	Medical	8.32	6.61	7.11	-0.27	9.47	2.44	0.28	-0.63	-0.07	-0.90
	Koran	0.65	0.47	-0.09	-0.21	-0.86	1.05	0.93	-0.01	-0.18	-0.08
	IT	5.89	6.17	6.76	-0.22	10.38	2.72	-0.78	-0.04	-0.11	-0.81
→en	Medical	-1.02	-0.05	-0.82	-0.29	-1.50	-0.65	-0.42	-0.11	-0.06	-0.18
	Koran	6.07	5.92	5.95	-0.20	8.28	0.97	-0.91	0.13	-0.14	-0.40

model knowledge harmlessly, avoiding issues such as catastrophic forgetting. Notably, they also explain the non-significant differences in BERTScore observed in Tables 1 and 2, since representation-level evaluation methods are not sensitive to word-level changes. In contrast, the consistent improvements in NIST scores highlight CDPG's effectiveness in conservatively enhancing domain-specific term usage.

However, these findings do not imply that CDPG benefits only word selection. In *Thesis* of en→zh, Pre-trained exhibits issues such as semantic loss and repetitive generation, whereas CDPG complements the missing semantics and mitigates the repetition. This improvement may be attributed to the enhanced confidence provided by GDC. Similarly, in the short sentence from en→zh, Pre-trained tends to translate the source into Chinese idioms that do not fully align semantically with the original sentence, i.e., ignoring the semantics of the word "suggestion". In contrast, CDPG correctly translates the key terms, suggesting that GDC enhances the model's focus on important words. In addition, in the long sentence of en→zh, the blue words represent an error in translation. This occurs because CDPG translates "transcendental" and "mapping" separately, as both words are present in the given features. This suggests that, since CDPG acts as a soft constraint, its use of keywords is not strictly enforced, but applied in a conservative manner.

6.3 Will Other Domains Be Influenced?

The primary goal of CDPG is to encourage the distribution of the pre-trained model to align with the expectations of the given features. However, since CDPG fits the model to a single domain, there is a potential risk of reduced generalization to other domains. Therefore, as shown in Table 7, we conduct experiments to measure the performance changes of Dynamic CDPG across domains from two perspectives: (1) the relative difference between Fine-tuned and Dynamic CDPG in the experimented domains; and (2) the change in performance of both Fine-tuned and Dynamic CDPG on a generic domain.

First, Fine-tuned consistently shows a decrease in both confidence and performance on the generic domain, whereas Dynamic CDPG achieves a significant increase in confidence in most cases, albeit with some fluctuations in performance. This indicates that the improvements achieved by our method generalize well, likely due to its intentionally conservative updates. While Dynamic CDPG generally demonstrates better generalization than Fine-tuned, there are two types of exceptions: (1) Changes in confidence can affect generalization, as CDPG induces a global increase in confidence rather than domain-specific gains. However,

Table 8: Scores from experiments with mixed-domain data from two domains. The *main domain* data is fixed, and sentences from a *mixed domain* are added during feature construction. The model is then evaluated only on the main domain data. #Sent. indicates the number of added sentences from the mixed domain. The best value for each domain block (across different #Sent. settings) is shown in **bold**.

English→German (Main: *IT*, Mix: *Medical*)

Method	#Sent.	Conf.	BLEU	P	R	F1
Fine-tuned	0	67.91	**27.92**	**87.38**	**87.60**	**87.42**
	500	67.82	27.63	87.35	87.57	87.39
	1,000	67.75	27.61	87.36	87.58	87.40
	2,000	67.61	27.27	87.32	87.55	87.36
CDPG	0	74.44	29.01	87.68	87.77	87.67
	500	74.24	**29.70**	**87.70**	**87.80**	**87.70**
	1,000	74.22	28.83	87.63	87.77	87.64
	2,000	74.14	29.43	87.68	87.79	87.68

English→Chinese (Main: *Thesis*, Mix: *Laws*)

Method	#Sent.	Conf.	BLEU	P	R	F1
Fine-tuned	0	47.23	**19.94**	76.42	**75.75**	**75.99**
	750	47.14	19.77	**76.44**	75.73	75.98
	1,500	47.05	19.63	76.42	**75.75**	75.98
	3,000	46.83	19.13	76.37	75.74	75.95
CDPG	0	54.19	19.94	76.11	75.53	75.72
	750	54.16	20.06	**76.25**	**75.59**	**75.81**
	1,500	54.12	**20.15**	76.21	**75.59**	75.80
	3,000	54.01	20.10	76.24	75.58	75.80

this indirect influence is generally limited. For example, although the largest BLEU score drop caused by increased confidence is 1.13 on *Koran* of `en→de`, Dynamic CDPG achieves a 2.86 BLEU improvement on *IT*, which is significantly better than Fine-tuned. (2) Performance in aligned cases is lower than in some cross-domain settings, such as *Thesis* of `en→zh` and *Medical* of `en→de`, suggesting that the provided *dev features* can have a negative impact. These results once again corroborate our analysis in Section 6.1, showing that the effectiveness of CDPG is closely tied to the quality and nature of the provided features.

Finally, we simulate a more realistic setting where the prepared data is not perfectly clean and may include content outside the target domain. We demonstrate the robustness of CDPG by comparing its performance trends to those of Fine-tuned in mixed-domain scenarios, where an extra domain dataset is intentionally introduced during tuning as contamination. Table 8 shows the results under several contamination settings. The results reveal that the performance of Fine-tuned consistently declines as the degree of domain mixing increases. In contrast, the performance of CDPG remains stable regardless of the domain mixture.

These findings suggest that, due to its conservative tuning approach, CDPG is less prone to issues such as catastrophic forgetting and overfitting. Moreover, even under more realistic conditions involving data contamination, CDPG achieves robust domain adaptation using only a small amount of monolingual data and target-side lexical distributions, outperforming typical fine-tuning methods that rely on parallel data.

7 Limitations

We conduct a comprehensive analysis; however, we acknowledge two main limitations in this work.

First, as stated in Sections 5 and 6.2, representation-level MT evaluation methods are not sensitive to the improvements made by CDPG, which results in only minor differences in BERTScore in particular. Moreover, although NIST provides a more reasonable assessment of domain-specific terminology and aligns more closely with our objectives, it remains limited by its BLEU-style surface-level representation design. Therefore, exploring how semantic-level evaluation methods can better capture word-specific changes remains an important direction for future work. Additionally, we did not include modern neural fine-tuned metrics, such as COMET (Rei et al., 2020) and BLEURT (Sellam et al., 2020), as part of our main evaluation. These metrics are fine-tuned on human-generated MT quality annotation data (Ma et al., 2019), but such data often fails to capture subtle patterns such as named entity differences (Amrhein & Sennrich, 2022; Glushkova et al., 2023). Moreover, due to overfitting to the annotation data, these metrics tend to favor outputs that are closer to the in-domain data of their fine-tuning sets (Zouhar et al., 2024a;b). Consequently, we determined that such fine-tuned metrics are not suitable for evaluating domain adaptation experiments.

Second, our primary goal is to demonstrate a novel practical application of massive EBMs using CDPG in a downstream task, with domain adaptation for machine translation as a case study. To maintain a clear focus on this objective, we adopted simple encoder-decoder architecture NMT models (Tiedemann &

Thottingal, 2020). We did not employ multilingual large models such as NLLB-200 (Team et al., 2022) or M2M100 (Fan et al., 2021), as they introduce additional complexity, including translation issues arising from multilingualism. Furthermore, extending our approach to translation-specific decoder-only large language models (Alves et al., 2024; Xu et al., 2025; Feng et al., 2025; Cui et al., 2025) or applying it to other domain datasets (Oncevay et al., 2025; Zhang et al., 2025; Cui et al., 2025) was not feasible given our available computational resources and would have made it harder to isolate the core effects of our method. Nonetheless, we believe our experiments already provide a comprehensive demonstration of the method's applicability and sufficiently address our research question. While such extensions remain promising future directions, we believe this work is a valuable pioneering study that lays the groundwork for broader applications.

8 Related Work

When using parallel data, Luong & Manning (2015); Freitag & Al-Onaizan (2016) perform domain adaptation by first training on large-scale general-domain data, then fine-tuning on a small amount of in-domain data. Chu et al. (2017) instead mix general and in-domain data for training at once. Further efficiency in domain adaptation has been pursued through techniques such as adding domain tags (Kobus et al., 2017; Britz et al., 2017), subword-aware tokenization (Enomoto et al., 2023), and training data sampling (Wang et al., 2017). However, direct fine-tuning with a small amount of data often leads to overfitting, prompting proposals of knowledge distillation (Dakwale & Monz, 2017) and regularization strategies (Miceli Barone et al., 2017).

In the context of monolingual data utilization, several methods have been explored such as back translation (Sennrich et al., 2016), direct learning from monolingual data as LM (Gulcehre et al., 2015; Zhang & Zong, 2016; Domhan & Hieber, 2017; Burlot & Yvon, 2018), exploiting task-specific features (Dou et al., 2019b;a), utilizing knowledge graphs (Moussallem et al., 2019; Zhao et al., 2020; Costa et al., 2022; Conia et al., 2024), and nearest neighbor search (Farajian et al., 2017; Bapna & Firat, 2019; Zheng et al., 2021; Khandelwal et al., 2021; Wang et al., 2022; Deguchi et al., 2023; Agrawal et al., 2023), and the combination of unsupervised NMT methods and back-translation technique (Mahdieh et al., 2020; Zhang et al., 2022). However, these approaches usually require large-scale monolingual data, which is not always available in specialized domains. Therefore, they may not be suitable for the extremely low-resource domain adaptation settings.

For terminology-constrained decoding, hard-constrained decoding methods (Hokamp & Liu, 2017; Post & Vilar, 2018; Hu et al., 2019; Post et al., 2019), which force the model to decode specific terminology, and soft-constrained decoding methods (Song et al., 2019; Chen et al., 2020), which apply post-editing techniques using phrase tables, have been proposed. However, since these approaches require predefined constrained vocabularies, they face challenges in real NMT scenarios that demand inductive domain adaptation.

CDPG (Korbak et al., 2022), which our study builds upon, focused only on minor input perturbations, e.g., replacing digits with spelled-out numbers, and did not address large-scale domain adaptation based on the full target-domain distribution. Regarding reinforcement learning methods (Ranzato et al., 2016; Kreutzer et al., 2017; Choshen et al., 2020; Yang et al., 2024), outside of the GDC framework, rewards are based only on overall scores such as BLEU, without the ability to impose fine-grained constraints. Furthermore, there is a potential for causing catastrophic forgetting, making scaling like in this study particularly challenging.

9 Conclusion

In this study, we explored whether unsupervised domain adaptation in machine translation can be effectively performed using only naive statistics, i.e., the monolingual lexical distribution, which can be easily obtained from target-side domain data without requiring bilingual supervision. We demonstrated this by imposing large-scale distributional constraints through EBMs at scale using the CDPG method, leveraging features derived from the entire target-domain corpus, and confirmed its effectiveness across multiple domains and language directions. This work is the first to demonstrate the practical applicability of CDPG of the GDC framework to a realistic downstream task, using the unsupervised domain adaptation of pre-trained NMT models as a case study. Although this work focused on word-level lexical distributions as the guiding signal, we believe that future work should explore alternative or complementary feature representations, such as n-gram statistics or language model embeddings, to further enhance fine-tuning within the GDC framework.

References

Sweta Agrawal, Chunting Zhou, Mike Lewis, Luke Zettlemoyer, and Marjan Ghazvininejad. In-context examples selection for machine translation. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), Findings of the Association for Computational Linguistics: ACL 2023, pp. 8857–8873, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-acl.564. URL https://aclanthology.org/2023.findings-acl.564/.

Roee Aharoni and Yoav Goldberg. Unsupervised domain clusters in pretrained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, 2020. URL https://arxiv.org/abs/2004.02105.

Farhad Akhbardeh, Arkady Arkhangorodsky, Magdalena Biesialska, Ondřej Bojar, Rajen Chatterjee, Vishrav Chaudhary, Marta R. Costa-jussa, Cristina España-Bonet, Angela Fan, Christian Federmann, Markus Freitag, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Leonie Harter, Kenneth Heafield, Christopher Homan, Matthias Huck, Kwabena Amponsah-Kaakyire, Jungo Kasai, Daniel Khashabi, Kevin Knight, Tom Kocmi, Philipp Koehn, Nicholas Lourie, Christof Monz, Makoto Morishita, Masaaki Nagata, Ajay Nagesh, Toshiaki Nakazawa, Matteo Negri, Santanu Pal, Allahsera Auguste Tapo, Marco Turchi, Valentin Vydrin, and Marcos Zampieri. Findings of the 2021 conference on machine translation (WMT21). In Loic Barrault, Ondrej Bojar, Fethi Bougares, Rajen Chatterjee, Marta R. Costa-jussa, Christian Federmann, Mark Fishel, Alexander Fraser, Markus Freitag, Yvette Graham, Roman Grundkiewicz, Paco Guzman, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Tom Kocmi, Andre Martins, Makoto Morishita, and Christof Monz (eds.), Proceedings of the Sixth Conference on Machine Translation, pp. 1–88, Online, November 2021. Association for Computational Linguistics. URL https://aclanthology.org/2021.wmt-1.1/.

Duarte Miguel Alves, José Pombal, Nuno M Guerreiro, Pedro Henrique Martins, João Alves, Amin Farajian, Ben Peters, Ricardo Rei, Patrick Fernandes, Sweta Agrawal, Pierre Colombo, José G. C. de Souza, and Andre Martins. Tower: An open multilingual large language model for translation-related tasks. In First Conference on Language Modeling, 2024. URL https://openreview.net/forum?id=EHPns3hVkj.

Chantal Amrhein and Rico Sennrich. Identifying weaknesses in machine translation metrics through minimum Bayes risk decoding: A case study for COMET. In Yulan He, Heng Ji, Sujian Li, Yang Liu, and Chua-Hui Chang (eds.), Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pp. 1125–1141, Online only, November 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.aacl-main.83. URL https://aclanthology.org/2022.aacl-main.83/.

Marta Bañón, Pinzhen Chen, Barry Haddow, Kenneth Heafield, Hieu Hoang, Miquel Esplà-Gomis, Mikel L. Forcada, Amir Kamran, Faheem Kirefu, Philipp Koehn, Sergio Ortiz Rojas, Leopoldo Pla Sempere, Gema Ramírez-Sánchez, Elsa Sarrías, Marek Strelec, Brian Thompson, William Waites, Dion Wiggins, and Jaume Zaragoza. ParaCrawl: Web-scale acquisition of parallel corpora. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 4555–4567, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.417. URL https://aclanthology.org/2020.acl-main.417/.

Ankur Bapna and Orhan Firat. Non-parametric adaptation for neural machine translation. In Jill Burstein, Christy Doran, and Thamar Solorio (eds.), Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 1921–1931, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1191. URL https://aclanthology.org/N19-1191/.

Loïc Barrault, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. Findings of the 2019 conference on machine translation (WMT19). In Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, André Martins, Christof Monz, Matteo Negri,

Aurélie Névéol, Mariana Neves, Matt Post, Marco Turchi, and Karin Verspoor (eds.), Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pp. 1–61, Florence, Italy, August 2019. Association for Computational Linguistics. doi: 10.18653/v1/W19-5301. URL https://aclanthology.org/W19-5301/.

Loïc Barrault, Magdalena Biesialska, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Matthias Huck, Eric Joanis, Tom Kocmi, Philipp Koehn, Chi-kiu Lo, Nikola Ljubešić, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Santanu Pal, Matt Post, and Marcos Zampieri. Findings of the 2020 conference on machine translation (WMT20). In Loïc Barrault, Ondřej Bojar, Fethi Bougares, Rajen Chatterjee, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Alexander Fraser, Yvette Graham, Paco Guzman, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, André Martins, Makoto Morishita, Christof Monz, Masaaki Nagata, Toshiaki Nakazawa, and Matteo Negri (eds.), Proceedings of the Fifth Conference on Machine Translation, pp. 1–55, Online, November 2020. Association for Computational Linguistics. URL https://aclanthology.org/2020.wmt-1.1/.

Dan Biderman, Jacob Portes, Jose Javier Gonzalez Ortiz, Mansheej Paul, Philip Greengard, Connor Jennings, Daniel King, Sam Havens, Vitaliy Chiley, Jonathan Frankle, Cody Blakeney, and John Patrick Cunningham. LoRA learns less and forgets less. Transactions on Machine Learning Research, 2024. ISSN 2835-8856. URL https://openreview.net/forum?id=aloEru2qCG. Featured Certification.

Ondřej Bojar, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, and Christof Monz. Findings of the 2018 conference on machine translation (WMT18). In Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Christof Monz, Matteo Negri, Aurélie Névéol, Mariana Neves, Matt Post, Lucia Specia, Marco Turchi, and Karin Verspoor (eds.), Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pp. 272–303, Belgium, Brussels, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6401. URL https://aclanthology.org/W18-6401/.

Denny Britz, Quoc Le, and Reid Pryzant. Effective domain mixing for neural machine translation. In Ondřej Bojar, Christian Buck, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, and Julia Kreutzer (eds.), Proceedings of the Second Conference on Machine Translation, pp. 118–126, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-4712. URL https://aclanthology.org/W17-4712/.

Franck Burlot and François Yvon. Using monolingual data in neural machine translation: a systematic study. In Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Christof Monz, Matteo Negri, Aurélie Névéol, Mariana Neves, Matt Post, Lucia Specia, Marco Turchi, and Karin Verspoor (eds.), Proceedings of the Third Conference on Machine Translation: Research Papers, pp. 144–155, Brussels, Belgium, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6315. URL https://aclanthology.org/W18-6315/.

Guanhua Chen, Yun Chen, Yong Wang, and Victor O.K. Li. Lexical-constraint-aware neural machine translation via data augmentation. In Christian Bessiere (ed.), Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, pp. 3587–3593. International Joint Conferences on Artificial Intelligence Organization, 7 2020. doi: 10.24963/ijcai.2020/496. URL https://doi.org/10.24963/ijcai.2020/496. Main track.

Leshem Choshen, Lior Fox, Zohar Aizenbud, and Omri Abend. On the weaknesses of reinforcement learning for neural machine translation. In International Conference on Learning Representations, 2020. URL https://openreview.net/forum?id=H1eCw3EKvH.

Chenhui Chu and Rui Wang. A survey of domain adaptation for neural machine translation. In Emily M. Bender, Leon Derczynski, and Pierre Isabelle (eds.), Proceedings of the 27th International Conference on Computational Linguistics, pp. 1304–1319, Santa Fe, New Mexico, USA, August 2018. Association for Computational Linguistics. URL https://aclanthology.org/C18-1111/.

Chenhui Chu, Raj Dabre, and Sadao Kurohashi. An empirical comparison of domain adaptation methods for neural machine translation. In Regina Barzilay and Min-Yen Kan (eds.), Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pp. 385–391, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-2061. URL https://aclanthology.org/P17-2061/.

Simone Conia, Daniel Lee, Min Li, Umar Farooq Minhas, Saloni Potdar, and Yunyao Li. Towards cross-cultural machine translation with retrieval-augmented generation from multilingual knowledge graphs. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, pp. 16343–16360, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.914. URL https://aclanthology.org/2024.emnlp-main.914/.

Alexandre Diniz da Costa, Mateus Coutinho Marim, Ely Matos, and Tiago Timponi Torrent. Domain adaptation in neural machine translation using a qualia-enriched FrameNet. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Jan Odijk, and Stelios Piperidis (eds.), Proceedings of the Thirteenth Language Resources and Evaluation Conference, pp. 1–12, Marseille, France, June 2022. European Language Resources Association. URL https://aclanthology.org/2022.lrec-1.1/.

Menglong Cui, Pengzhi Gao, Wei Liu, Jian Luan, and Bin Wang. Multilingual machine translation with open large language models at practical scale: An empirical study. In Luis Chiruzzo, Alan Ritter, and Lu Wang (eds.), Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pp. 5420–5443, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 979-8-89176-189-6. doi: 10.18653/v1/2025.naacl-long.280. URL https://aclanthology.org/2025.naacl-long.280/.

Praveen Dakwale and Christof Monz. Fine-tuning for neural machine translation with limited degradation across in- and out-of-domain data. In Sadao Kurohashi and Pascale Fung (eds.), Proceedings of Machine Translation Summit XVI: Research Track, pp. 156–169, Nagoya Japan, September 18 – September 22 2017. URL https://aclanthology.org/2017.mtsummit-papers.13/.

Hiroyuki Deguchi, Taro Watanabe, Yusuke Matsui, Masao Utiyama, Hideki Tanaka, and Eiichiro Sumita. Subset retrieval nearest neighbor machine translation. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 174–189, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.10. URL https://aclanthology.org/2023.acl-long.10/.

George Doddington. Automatic evaluation of machine translation quality using n-gram co-occurrence statistics. In Proceedings of the Second International Conference on Human Language Technology Research, HLT '02, pp. 138–145, San Francisco, CA, USA, 2002. Morgan Kaufmann Publishers Inc.

Tobias Domhan and Felix Hieber. Using target-side monolingual data for neural machine translation through multi-task learning. In Martha Palmer, Rebecca Hwa, and Sebastian Riedel (eds.), Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pp. 1500–1505, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1158. URL https://aclanthology.org/D17-1158/.

Zi-Yi Dou, Junjie Hu, Antonios Anastasopoulos, and Graham Neubig. Unsupervised domain adaptation for neural machine translation with domain-aware feature embeddings. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan (eds.), Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pp. 1417–1422, Hong Kong, China, November 2019a. Association for Computational Linguistics. doi: 10.18653/v1/D19-1147. URL https://aclanthology.org/D19-1147/.

Zi-Yi Dou, Xinyi Wang, Junjie Hu, and Graham Neubig. Domain differential adaptation for neural machine translation. In Alexandra Birch, Andrew Finch, Hiroaki Hayashi, Ioannis Konstas, Thang Luong, Graham

Neubig, Yusuke Oda, and Katsuhito Sudoh (eds.), Proceedings of the 3rd Workshop on Neural Generation and Translation, pp. 59–69, Hong Kong, November 2019b. Association for Computational Linguistics. doi: 10.18653/v1/D19-5606. URL https://aclanthology.org/D19-5606/.

Taisei Enomoto, Tosho Hirasawa, Hwichan Kim, Teruaki Oka, and Mamoru Komachi. Simultaneous domain adaptation of tokenization and machine translation. In Chu-Ren Huang, Yasunari Harada, Jong-Bok Kim, Si Chen, Yu-Yin Hsu, Emmanuele Chersoni, Pranav A, Winnie Huiheng Zeng, Bo Peng, Yuxi Li, and Junlin Li (eds.), Proceedings of the 37th Pacific Asia Conference on Language, Information and Computation, pp. 36–45, Hong Kong, China, December 2023. Association for Computational Linguistics. URL https://aclanthology.org/2023.paclic-1.4/.

Angela Fan, Shruti Bhosale, Holger Schwenk, Zhiyi Ma, Ahmed El-Kishky, Siddharth Goyal, Mandeep Baines, Onur Celebi, Guillaume Wenzek, Vishrav Chaudhary, Naman Goyal, Tom Birch, Vitaliy Liptchinsky, Sergey Edunov, Michael Auli, and Armand Joulin. Beyond english-centric multilingual machine translation. Journal of Machine Learning Research, 22(107):1–48, 2021. URL http://jmlr.org/papers/v22/20-1307.html.

M. Amin Farajian, Marco Turchi, Matteo Negri, and Marcello Federico. Multi-domain neural machine translation through unsupervised adaptation. In Ondřej Bojar, Christian Buck, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, and Julia Kreutzer (eds.), Proceedings of the Second Conference on Machine Translation, pp. 127–137, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-4713. URL https://aclanthology.org/W17-4713/.

Zhaopeng Feng, Yan Zhang, Hao Li, Bei Wu, Jiayu Liao, Wenqiang Liu, Jun Lang, Yang Feng, Jian Wu, and Zuozhu Liu. TEaR: Improving LLM-based machine translation with systematic self-refinement. In Luis Chiruzzo, Alan Ritter, and Lu Wang (eds.), Findings of the Association for Computational Linguistics: NAACL 2025, pp. 3922–3938, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 979-8-89176-195-7. doi: 10.18653/v1/2025.findings-naacl.218. URL https://aclanthology.org/2025.findings-naacl.218/.

Markus Freitag and Yaser Al-Onaizan. Fast domain adaptation for neural machine translation, 2016.

Victoria M. Garlock, Amanda C. Walley, and Jamie L. Metsala. Age-of-acquisition, word frequency, and neighborhood density effects on spoken word recognition by children and adults. Journal of Memory and Language, 45(3):468–492, 2001. ISSN 0749-596X. doi: https://doi.org/10.1006/jmla.2000.2784. URL https://www.sciencedirect.com/science/article/pii/S0749596X00927840.

Taisiya Glushkova, Chrysoula Zerva, and André F. T. Martins. BLEU meets COMET: Combining lexical and neural metrics towards robust machine translation evaluation. In Mary Nurminen, Judith Brenner, Maarit Koponen, Sirkku Latomaa, Mikhail Mikhailov, Frederike Schierl, Tharindu Ranasinghe, Eva Vanmassenhove, Sergi Alvarez Vidal, Nora Aranberri, Mara Nunziatini, Carla Parra Escartín, Mikel Forcada, Maja Popovic, Carolina Scarton, and Helena Moniz (eds.), Proceedings of the 24th Annual Conference of the European Association for Machine Translation, pp. 47–58, Tampere, Finland, June 2023. European Association for Machine Translation. URL https://aclanthology.org/2023.eamt-1.6/.

Shuhao Gu and Yang Feng. Investigating catastrophic forgetting during continual training for neural machine translation. In Donia Scott, Nuria Bel, and Chengqing Zong (eds.), Proceedings of the 28th International Conference on Computational Linguistics, pp. 4315–4326, Barcelona, Spain (Online), December 2020. International Committee on Computational Linguistics. doi: 10.18653/v1/2020.coling-main.381. URL https://aclanthology.org/2020.coling-main.381/.

Caglar Gulcehre, Orhan Firat, Kelvin Xu, Kyunghyun Cho, Loic Barrault, Huei-Chi Lin, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. On using monolingual corpora in neural machine translation, 2015. *arXiv preprint* arXiv:1503.03535.

Chris Hokamp and Qun Liu. Lexically constrained decoding for sequence generation using grid beam search. In Regina Barzilay and Min-Yen Kan (eds.), Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 1535–1546, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1141. URL https://aclanthology.org/P17-1141/.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. In International Conference on Learning Representations, 2020. URL https://openreview.net/forum?id=rygGQyrFvH.

Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In International Conference on Learning Representations, 2022. URL https://openreview.net/forum?id=nZeVKeeFYf9.

J. Edward Hu, Huda Khayrallah, Ryan Culkin, Patrick Xia, Tongfei Chen, Matt Post, and Benjamin Van Durme. Improved lexically constrained decoding for translation and monolingual rewriting. In Jill Burstein, Christy Doran, and Thamar Solorio (eds.), Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 839–850, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1090. URL https://aclanthology.org/N19-1090/.

Muhammad Khalifa, Hady Elsahar, and Marc Dymetman. A distributional approach to controlled text generation. In International Conference on Learning Representations, 2021. URL https://openreview.net/forum?id=jWkw45-9AbL.

Urvashi Khandelwal, Angela Fan, Dan Jurafsky, Luke Zettlemoyer, and Mike Lewis. Nearest neighbor machine translation. In International Conference on Learning Representations, 2021. URL https://openreview.net/forum?id=7wCBOfJ8hJM.

Samuel Kiegeland and Julia Kreutzer. Revisiting the weaknesses of reinforcement learning for neural machine translation. In Kristina Toutanova, Anna Rumshisky, Luke Zettlemoyer, Dilek Hakkani-Tur, Iz Beltagy, Steven Bethard, Ryan Cotterell, Tanmoy Chakraborty, and Yichao Zhou (eds.), Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 1673–1681, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.133. URL https://aclanthology.org/2021.naacl-main.133/.

Adam Kilgarriff. Using word frequency lists to measure corpus homogeneity and similarity between corpora. In Fifth Workshop on Very Large Corpora, 1997. URL https://aclanthology.org/W97-0122/.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017. *arXiv preprint* arXiv:1412.6980.

Catherine Kobus, Josep Crego, and Jean Senellart. Domain control for neural machine translation. In Ruslan Mitkov and Galia Angelova (eds.), Proceedings of the International Conference Recent Advances in Natural Language Processing, RANLP 2017, pp. 372–378, Varna, Bulgaria, September 2017. INCOMA Ltd. doi: 10.26615/978-954-452-049-6_049. URL https://aclanthology.org/R17-1049/.

Tom Kocmi, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Thamme Gowda, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Rebecca Knowles, Philipp Koehn, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Michal Novák, Martin Popel, and Maja Popović. Findings of the 2022 conference on machine translation (WMT22). In Philipp Koehn, Loïc Barrault, Ondřej Bojar, Fethi Bougares, Rajen Chatterjee, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Alexander Fraser, Markus Freitag, Yvette Graham, Roman Grundkiewicz, Paco Guzman, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Tom Kocmi, André Martins, Makoto Morishita, Christof Monz, Masaaki Nagata, Toshiaki Nakazawa, Matteo Negri, Aurélie Névéol, Mariana Neves, Martin Popel, Marco Turchi, and Marcos Zampieri (eds.), Proceedings of the Seventh Conference on Machine Translation (WMT), pp. 1–45, Abu Dhabi, United Arab Emirates (Hybrid), December 2022. Association for Computational Linguistics. URL https://aclanthology.org/2022.wmt-1.1/.

Philipp Koehn and Rebecca Knowles. Six challenges for neural machine translation. In Thang Luong, Alexandra Birch, Graham Neubig, and Andrew Finch (eds.), Proceedings of the First Workshop on Neural Machine Translation, pp. 28–39, Vancouver, August 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-3204. URL https://aclanthology.org/W17-3204.

Tomasz Korbak, Hady Elsahar, German Kruszewski, and Marc Dymetman. Controlling conditional language models without catastrophic forgetting. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), Proceedings of the 39th International Conference on Machine Learning, volume 162 of Proceedings of Machine Learning Research, pp. 11499–11528. PMLR, 17–23 Jul 2022. URL https://proceedings.mlr.press/v162/korbak22a.html.

Julia Kreutzer, Artem Sokolov, and Stefan Riezler. Bandit structured prediction for neural sequence-to-sequence learning. In Regina Barzilay and Min-Yen Kan (eds.), Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 1503–1513, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1138. URL https://aclanthology.org/P17-1138/.

Germán Kruszewski, Jos Rozen, and Marc Dymetman. disco: a toolkit for distributional control of generative models. In Danushka Bollegala, Ruihong Huang, and Alan Ritter (eds.), Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations), pp. 144–160, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-demo.14. URL https://aclanthology.org/2023.acl-demo.14/.

Batia Laufer and Paul Nation. Vocabulary size and use: Lexical richness in l2 written production. Applied Linguistics, 16(3):307–322, 09 1995. ISSN 0142-6001. doi: 10.1093/applin/16.3.307. URL https://doi.org/10.1093/applin/16.3.307.

Minh-Thang Luong and Christopher Manning. Stanford neural machine translation systems for spoken language domains. In Marcello Federico, Sebastian Stüker, and Jan Niehues (eds.), Proceedings of the 12th International Workshop on Spoken Language Translation: Evaluation Campaign, pp. 76–79, Da Nang, Vietnam, December 3-4 2015. URL https://aclanthology.org/2015.iwslt-evaluation.11/.

Qingsong Ma, Johnny Wei, Ondřej Bojar, and Yvette Graham. Results of the WMT19 metrics shared task: Segment-level and strong MT systems pose big challenges. In Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, André Martins, Christof Monz, Matteo Negri, Aurélie Névéol, Mariana Neves, Matt Post, Marco Turchi, and Karin Verspoor (eds.), Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pp. 62–90, Florence, Italy, August 2019. Association for Computational Linguistics. doi: 10.18653/v1/W19-5302. URL https://aclanthology.org/W19-5302/.

Mahdis Mahdieh, Mia Xu Chen, Yuan Cao, and Orhan Firat. Rapid domain adaptation for machine translation with monolingual data, 2020. URL https://arxiv.org/abs/2010.12652.

Antonio Valerio Miceli Barone, Barry Haddow, Ulrich Germann, and Rico Sennrich. Regularization techniques for fine-tuning in neural machine translation. In Martha Palmer, Rebecca Hwa, and Sebastian Riedel (eds.), Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pp. 1489–1494, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1156. URL https://aclanthology.org/D17-1156/.

Makoto Morishita, Katsuki Chousa, Jun Suzuki, and Masaaki Nagata. JParaCrawl v3.0: A large-scale English-Japanese parallel corpus. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Jan Odijk, and Stelios Piperidis (eds.), Proceedings of the Thirteenth Language Resources and Evaluation Conference, pp. 6704–6710, Marseille, France, June 2022. European Language Resources Association. URL https://aclanthology.org/2022.lrec-1.721/.

Diego Moussallem, Axel-Cyrille Ngonga Ngomo, Paul Buitelaar, and Mihael Arcan. Utilizing knowledge graphs for neural machine translation augmentation. In Proceedings of the 10th International Conference on Knowledge Capture, K-CAP '19, pp. 139–146, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450370080. doi: 10.1145/3360901.3364423. URL https://doi.org/10.1145/3360901.3364423.

Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc., 2019. URL https://proceedings.neurips.cc/paper_files/paper/2019/file/f1748d6b0fd9d439f71450117eba2725-Paper.pdf.

Arturo Oncevay, Charese Smiley, and Xiaomo Liu. The impact of domain-specific terminology on machine translation for finance in European languages. In Luis Chiruzzo, Alan Ritter, and Lu Wang (eds.), Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pp. 2758–2775, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 979-8-89176-189-6. doi: 10.18653/v1/2025.naacl-long.140. URL https://aclanthology.org/2025.naacl-long.140/.

Jianhui Pang, Fanghua Ye, Derek Fai Wong, Dian Yu, Shuming Shi, Zhaopeng Tu, and Longyue Wang. Salute the classic: Revisiting challenges of machine translation in the age of large language models. Transactions of the Association for Computational Linguistics, 13:73–95, 2025. doi: 10.1162/tacl_a_00730. URL https://aclanthology.org/2025.tacl-1.4/.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pp. 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073135. URL https://aclanthology.org/P02-1040.

Matt Post. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pp. 186–191, Brussels, Belgium, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6319. URL https://aclanthology.org/W18-6319.

Matt Post and David Vilar. Fast lexically constrained decoding with dynamic beam allocation for neural machine translation. In Marilyn Walker, Heng Ji, and Amanda Stent (eds.), Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pp. 1314–1324, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1119. URL https://aclanthology.org/N18-1119/.

Matt Post, Shuoyang Ding, Marianna Martindale, and Winston Wu. An exploration of placeholding in neural machine translation. In Mikel Forcada, Andy Way, Barry Haddow, and Rico Sennrich (eds.), Proceedings of Machine Translation Summit XVII: Research Track, pp. 182–192, Dublin, Ireland, August 2019. European Association for Machine Translation. URL https://aclanthology.org/W19-6618/.

Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. Sequence level training with recurrent neural networks, 2016. *arXiv preprint* arXiv:1511.06732.

Vikas Raunak and Arul Menezes. Finding memo: Extractive memorization in constrained sequence generation tasks. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (eds.), Findings of the Association for Computational Linguistics: EMNLP 2022, pp. 5153–5162, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-emnlp.378. URL https://aclanthology.org/2022.findings-emnlp.378/.

Paul Rayson and Roger Garside. Comparing corpora using frequency profiling. In The Workshop on Comparing Corpora, pp. 1–6, Hong Kong, China, October 2000. Association for Computational Linguistics. doi: 10.3115/1117729.1117730. URL https://aclanthology.org/W00-0901/.

Ricardo Rei, Craig Stewart, Ana C Farinha, and Alon Lavie. COMET: A neural framework for MT evaluation. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu (eds.), Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 2685–2702, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.213. URL https://aclanthology.org/2020.emnlp-main.213/.

Danielle Saunders and Steve DeNeefe. Domain adapted machine translation: What does catastrophic forgetting forget and why? In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, pp. 12660–12671, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.704. URL https://aclanthology.org/2024.emnlp-main.704/.

Thibault Sellam, Dipanjan Das, and Ankur Parikh. BLEURT: Learning robust metrics for text generation. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 7881–7892, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.704. URL https://aclanthology.org/2020.acl-main.704/.

Rico Sennrich, Barry Haddow, and Alexandra Birch. Improving neural machine translation models with monolingual data. In Katrin Erk and Noah A. Smith (eds.), Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 86–96, Berlin, Germany, August 2016. Association for Computational Linguistics. doi: 10.18653/v1/P16-1009. URL https://aclanthology.org/P16-1009/.

Jiajun Shen, Peng-Jen Chen, Matthew Le, Junxian He, Jiatao Gu, Myle Ott, Michael Auli, and Marc'Aurelio Ranzato. The source-target domain mismatch problem in machine translation. In Paola Merlo, Jorg Tiedemann, and Reut Tsarfaty (eds.), Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pp. 1519–1533, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.130. URL https://aclanthology.org/2021.eacl-main.130/.

Kai Song, Yue Zhang, Heng Yu, Weihua Luo, Kun Wang, and Min Zhang. Code-switching for enhancing NMT with pre-specified translation. In Jill Burstein, Christy Doran, and Thamar Solorio (eds.), Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 449–459, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1044. URL https://aclanthology.org/N19-1044/.

NLLB Team, Marta R. Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, Anna Sun, Skyler Wang, Guillaume Wenzek, Al Youngblood, Bapi Akula, Loic Barrault, Gabriel Mejia Gonzalez, Prangthip Hansanti, John Hoffman, Semarley Jarrett, Kaushik Ram Sadagopan, Dirk Rowe, Shannon Spruit, Chau Tran, Pierre Andrews, Necip Fazil Ayan, Shruti Bhosale, Sergey Edunov, Angela Fan, Cynthia Gao, Vedanuj Goswami, Francisco Guzmán, Philipp Koehn, Alexandre Mourachko, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, and Jeff Wang. No language left behind: Scaling human-centered machine translation, 2022. URL https://arxiv.org/abs/2207.04672.

Brian Thompson, Jeremy Gwinnup, Huda Khayrallah, Kevin Duh, and Philipp Koehn. Overcoming catastrophic forgetting during domain adaptation of neural machine translation. In Jill Burstein, Christy Doran, and Thamar Solorio (eds.), Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 2062–2068, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1209. URL https://aclanthology.org/N19-1209/.

Liang Tian, Derek F. Wong, Lidia S. Chao, Paulo Quaresma, Francisco Oliveira, Yi Lu, Shuo Li, Yiming Wang, and Longyue Wang. UM-corpus: A large English-Chinese parallel corpus for statistical machine translation. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Hrafn Loftsson, Bente Maegaard,

Joseph Mariani, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), pp. 1837–1842, Reykjavik, Iceland, May 2014. European Language Resources Association (ELRA). URL http://www.lrec-conf.org/proceedings/lrec2014/pdf/774_Paper.pdf.

Jörg Tiedemann. Parallel data, tools and interfaces in OPUS. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Mehmet Uğur Doğan, Bente Maegaard, Joseph Mariani, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12), pp. 2214–2218, Istanbul, Turkey, May 2012. European Language Resources Association (ELRA). URL https://aclanthology.org/L12-1246/.

Jörg Tiedemann and Santhosh Thottingal. OPUS-MT — Building open translation services for the World. In Proceedings of the 22nd Annual Conferenec of the European Association for Machine Translation (EAMT), Lisbon, Portugal, 2020.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 30. Curran Associates, Inc., 2017. URL https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.

Dexin Wang, Kai Fan, Boxing Chen, and Deyi Xiong. Efficient cluster-based k-nearest-neighbor machine translation. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 2175–2187, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.154. URL https://aclanthology.org/2022.acl-long.154/.

Rui Wang, Andrew Finch, Masao Utiyama, and Eiichiro Sumita. Sentence embedding for neural machine translation domain adaptation. In Regina Barzilay and Min-Yen Kan (eds.), Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pp. 560–566, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-2089. URL https://aclanthology.org/P17-2089/.

Shuo Wang, Zhaopeng Tu, Shuming Shi, and Yang Liu. On the inference calibration of neural machine translation. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 3070–3079, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.278. URL https://aclanthology.org/2020.acl-main.278/.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In Qun Liu and David Schlangen (eds.), Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pp. 38–45, Online, October 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-demos.6. URL https://aclanthology.org/2020.emnlp-demos.6/.

Haoran Xu, Kenton Murray, Philipp Koehn, Hieu Hoang, Akiko Eriguchi, and Huda Khayrallah. X-ALMA: Plug & play modules and adaptive rejection for quality translation at scale. In The Thirteenth International Conference on Learning Representations, 2025. URL https://openreview.net/forum?id=csbf1p8xUq.

Lingling Xu, Haoran Xie, Si-Zhao Joe Qin, Xiaohui Tao, and Fu Lee Wang. Parameter-efficient fine-tuning methods for pretrained language models: A critical review and assessment, 2023. URL https://arxiv.org/abs/2312.12148.

Guangyu Yang, Jinghong Chen, Weizhe Lin, and Bill Byrne. Direct preference optimization for neural machine translation with minimum Bayes risk decoding. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 2: Short Papers), pp. 391–398, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-short.34. URL https://aclanthology.org/2024.naacl-short.34/.

Lana Yeganova, Dina Wiemann, Mariana Neves, Federica Vezzani, Amy Siu, Inigo Jauregi Unanue, Maite Oronoz, Nancy Mah, Aurélie Névéol, David Martinez, Rachel Bawden, Giorgio Maria Di Nunzio, Roland Roller, Philippe Thomas, Cristian Grozea, Olatz Perez-de Viñaspre, Maika Vicente Navarro, and Antonio Jimeno Yepes. Findings of the WMT 2021 biomedical translation shared task: Summaries of animal experiments as new test set. In Loic Barrault, Ondrej Bojar, Fethi Bougares, Rajen Chatterjee, Marta R. Costa-jussa, Christian Federmann, Mark Fishel, Alexander Fraser, Markus Freitag, Yvette Graham, Roman Grundkiewicz, Paco Guzman, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Tom Kocmi, Andre Martins, Makoto Morishita, and Christof Monz (eds.), Proceedings of the Sixth Conference on Machine Translation, pp. 664–683, Online, November 2021. Association for Computational Linguistics. URL https://aclanthology.org/2021.wmt-1.70/.

Hongxiao Zhang, Hui Huang, Jiale Gao, Yufeng Chen, Jinan Xu, and Jian Liu. Iterative constrained back-translation for unsupervised domain adaptation of machine translation. In Nicoletta Calzolari, Chu-Ren Huang, Hansaem Kim, James Pustejovsky, Leo Wanner, Key-Sun Choi, Pum-Mo Ryu, Hsin-Hsi Chen, Lucia Donatelli, Heng Ji, Sadao Kurohashi, Patrizia Paggio, Nianwen Xue, Seokhwan Kim, Younggyun Hahm, Zhong He, Tony Kyungil Lee, Enrico Santus, Francis Bond, and Seung-Hoon Na (eds.), Proceedings of the 29th International Conference on Computational Linguistics, pp. 5054–5065, Gyeongju, Republic of Korea, October 2022. International Committee on Computational Linguistics. URL https://aclanthology.org/2022.coling-1.448/.

Jiajun Zhang and Chengqing Zong. Exploiting source-side monolingual data in neural machine translation. In Jian Su, Kevin Duh, and Xavier Carreras (eds.), Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 1535–1545, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1160. URL https://aclanthology.org/D16-1160/.

Ran Zhang, Wei Zhao, and Steffen Eger. How good are LLMs for literary translation, really? literary translation evaluation with humans and LLMs. In Luis Chiruzzo, Alan Ritter, and Lu Wang (eds.), Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pp. 10961–10988, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 979-8-89176-189-6. doi: 10.18653/v1/2025.naacl-long.548. URL https://aclanthology.org/2025.naacl-long.548/.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. BERTScore: Evaluating text generation with bert. In International Conference on Learning Representations, 2020. URL https://openreview.net/forum?id=SkeHuCVFDr.

Yang Zhao, Lu Xiang, Junnan Zhu, Jiajun Zhang, Yu Zhou, and Chengqing Zong. Knowledge graph enhanced neural machine translation via multi-task learning on sub-entity granularity. In Donia Scott, Nuria Bel, and Chengqing Zong (eds.), Proceedings of the 28th International Conference on Computational Linguistics, pp. 4495–4505, Barcelona, Spain (Online), December 2020. International Committee on Computational Linguistics. doi: 10.18653/v1/2020.coling-main.397. URL https://aclanthology.org/2020.coling-main.397/.

Xin Zheng, Zhirui Zhang, Shujian Huang, Boxing Chen, Jun Xie, Weihua Luo, and Jiajun Chen. Non-parametric unsupervised domain adaptation for neural machine translation. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), Findings of the Association for Computational Linguistics: EMNLP 2021, pp. 4234–4241, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.358. URL https://aclanthology.org/2021.findings-emnlp.358/.

Vilém Zouhar, Pinzhen Chen, Tsz Kin Lam, Nikita Moghe, and Barry Haddow. Pitfalls and outlooks in using COMET. In Barry Haddow, Tom Kocmi, Philipp Koehn, and Christof Monz (eds.), Proceedings of the Ninth Conference on Machine Translation, pp. 1272–1288, Miami, Florida, USA, November 2024a. Association for Computational Linguistics. doi: 10.18653/v1/2024.wmt-1.121. URL https://aclanthology.org/2024.wmt-1.121/.

Vilém Zouhar, Shuoyang Ding, Anna Currey, Tatyana Badeka, Jenyuan Wang, and Brian Thompson. Fine-tuned machine translation metrics struggle in unseen domains. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pp. 488–500, Bangkok, Thailand, August 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-short.45. URL https://aclanthology.org/2024.acl-short.45/.