Specializing Multi-domain NMT via Penalizing Low Mutual Information

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Abstract

Multi-domain Neural Machine Translation (NMT) trains a single model with multiple domains. It is appealing because of its efficacy in handling multiple domains within one model. An ideal multi-domain NMT should learn distinctive domain characteristics simultaneously, however, grasping the domain peculiarity is a non-trivial task. In this paper, we investigate domain-specific information through the lens of mutual information (MI) and propose a new objective that penalizes low MI to become higher. Our method achieved the state-of-the-art performance among the current competitive multi-domain NMT models. Also, we empirically show our objective promotes low MI to be higher resulting in domain-specialized multi-domain NMT.

1 Introduction

Multi-domain Neural Machine Translation (NMT) (Sajjad et al., 2017; Farajian et al., 2017) has been an attractive topic due to its efficacy in handling multiple domains with a single model. Ideally, a multi-domain NMT should capture both general knowledge (*e.g.*, sentence structure, common words) and domain-specific knowledge (*e.g.*, domain terminology) unique in each domain. While the shared knowledge can be easily acquired via sharing parameters across domains (Kobus et al., 2017), obtaining domain specialized knowledge is a challenging task. Haddow and Koehn (2012) demonstrate that a model trained on multiple domains sometimes underperforms the one trained on a single domain. Pham et al. (2021) shows that separate domain-specific adaptation modules are not sufficient to fully-gain specialized knowledge.

In this paper, we reinterpret domain specialized knowledge from mutual information (MI) perspective and propose a method to strengthen it. Given a source sentence X, target sentence Y, and corresponding domain D, the MI between D and the translation $Y|X$ (*i.e.*, $\text{MI}(D; Y|X)$) measures the dependency between the domain and the translated sentence. Here, we assume that the larger $\text{MI}(D; Y|X)$, the more the translation incorporates domain knowledge. Low MI is undesirable because it indicates the model is not sufficiently utilizing domain characteristics in translation. In other words, low MI can be interpreted as a domain-specific information the model has yet to learn. For example, as shown in Fig. 1, we found that a model with low MI translates an IT term 'computing totals' to the vague and plain term 'calculation'. However, once we force the model to have high MI, 'computing totals' is correctly retained in its translation. Thus, maximizing MI promotes multi-domain NMT to be domain-specialized.

Source	Beschreib ... **Summenberechnung** für ein gegebenes Feld oder einen gegebenen Ausdruck.
Reference	Describes a way of **computing totals** for a given field or expression.
A (Baseline)	Describes the kind of **calculation** for a given field or expression.
B (Ours)	Describes the way of **computing totals** for a given field or expression .

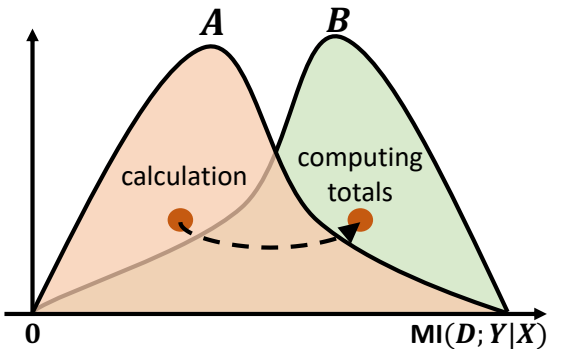

Figure 1: Overview of two models with different MI distributions. The example sentence is from IT domain. Model A mostly has low MI and Model B has large MI. For an identical sample, model A outputs a generic term 'calculation' while model B properly maintains 'computing totals'.

Motivated by this idea, we introduce a new method that specializes multi-domain NMT by

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penalizing low MI. We first theoretically derive $\text{MI}(D; Y|X)$, and formulate a new objective that weights more penalty on subword-tokens with low MI. Our results show that the proposed method improves the translation quality in all domains. Also, the MI visualization ensures that our method is effective in maximizing MI. We also observed that our model performs particularly better on samples with strong domain characteristics.

The main contributions of our paper are as follows:

- We investigate MI in multi-domain NMT and present a new objective that penalizes low MI to have higher value.
- Extensive experiment results prove that our method truly yields high MI, resulting in domain-specialized model.

2 Related Works

Multi-Domain Neural Machine Translation Multi-Domain NMT focuses on developing a proper usage of domain information to improve translation. Early studies had two main approaches: injecting source domain information and adding a domain classifier. For adding source domain information, Kobus et al. (2017) inserts a source domain label as an additional tag with input or as a complementary feature. For the second approach, Britz et al. (2017) trains the sentence embedding to be domain-specific by updating using the gradient from the domain-classifier.

While previous work leverages domain information by injection or implementing an auxiliary classifier, we view domain information from MI perspective and propose a loss that promotes model to explore domain specific knowledge.

Information-Theoretic Approaches in NMT Mutual information in NMT is primarily used either as metrics or a loss function. For metrics, Bugliarello et al. (2020) proposes cross-mutual information (XMI) to quantify the difficulty of translating between languages. Fernandes et al. (2021) modifies XMI to measure the usage of the given context during translation. For the loss function, Xu et al. (2021) proposes bilingual mutual information (BMI) which calculates the word mapping diversity, further applied in NMT training. Zhang et al. (2022) improves the model translation by maximizing the MI between a target token and its source sentence based on its context.

Above work only considers general machine translation scenarios. Our work differs in that we integrate mutual information in multi-domain NMT to learn domain-specific information. Unlike other methods that require training of an additional model, our method can calculate MI within a single model which is more computation-efficient.

3 Proposed Method

In this section, we first derive MI in multi-domain NMT. Then, we introduce a new method that penalizes low MI to have high value resulting in a domain-specialized model.

3.1 Mutual Information in Multi-Domain NMT

Mutual Information (MI) measures a mutual dependency between two random variables. In multi-domain NMT, the MI between the domain (D) and translation ($Y|X$), expressed as $\text{MI}(D; Y|X)$, represents how much domain-specific information is contained in the translation. $\text{MI}(D; Y|X)$ can be written as follows:

$$\text{MI}(D; Y|X) = \mathbb{E}_{D,X,Y}\left[\log \frac{p(Y|X, D)}{p(Y|X)}\right]. \quad (1)$$

The full derivation can be found in Appendix B. Note that the final form of $\text{MI}(D; Y|X)$ is a log quotient of the translation considering domain and translation without domain.

Since the true distributions are unknown, we approximate them with a parameterized model (Bugliarello et al., 2020; Fernandes et al., 2021), namely the cross-MI (XMI). Naturally, a generic domain-agnostic model (further referred to as *general* and abbreviated as *G*) output would be the appropriate approximation of $p(Y|X)$. A domain-adapted (further shortened as *DA*) model output would be suitable for $p(Y|X, D)$. Hence, $\text{XMI}(D; Y|X)$ can be expressed as Eq. (2) with each model output.

$$\text{XMI}(D; Y|X) = \mathbb{E}_{D,X,Y}\left[\log \frac{p_{DA}(Y|X, D)}{p_G(Y|X)}\right] \quad (2)$$

3.2 MI-based Token Weighted Loss

To calculate XMI, we need outputs from both general and domain-adapted models. Motivated by the success of adapters (Houlsby et al., 2019) in multi-domain NMT (Pham et al., 2021), we assign adapters $\phi_1, \cdots \phi_N$ for each domain (N is the total

number of domains) and have an extra adapter ϕ_G for general. We will denote the shared parameter (*e.g.*, self-attention and feed-forward layer) as θ. For a source sentence x from domain d, x passes the model twice, once through the corresponding domain adapter, ϕ_d, and the other through the general adapter, ϕ_G. Then, we treat the output probability from domain adapter as p_{DA} and from general adapter as p_G. For the i^{th} target token, y_i ,we calculate XMI as in Eq. (3),

$$p(y_i|y_{<i}, x, \theta, \phi_d) - p(y_i|y_{<i}, x, \theta, \phi_G) \quad (3)$$

, where $y_{<i}$ is the target subword-tokens up to, but excluding y_i. For simplicity, we will denote Eq. (3) as XMI(i). Low XMI(i) means that our domain adapted model is not thoroughly utilizing domain information during translation. Therefore, we weight more on the tokens with low XMI(i), resulting in minimizing Eq. (4),

$$\mathcal{L}_{\text{MI}} = \sum_{i=0}^{n_T} (1 - \text{XMI}(i)) \cdot (1 - p(y_i|y_{<i}, x, \theta, \phi_d)) \quad (4)$$

, where n_T is the number of subword-tokens in the target sentence.

The final loss of our method is in Eq. (7), where λ_1 and λ_2 are hyperparameters.

$$\mathcal{L}_{\text{DA}} = -\sum_{i=0}^{n_T} \log(p(y_i|y_{<i}, x, \theta, \phi_d)) \quad (5)$$

$$\mathcal{L}_{\text{G}} = -\sum_{i=0}^{n_T} \log(p(y_i|y_{<i}, x, \theta, \phi_G)) \quad (6)$$

$$\mathcal{L} = \mathcal{L}_{\text{DA}} + \lambda_1 \mathcal{L}_{\text{G}} + \lambda_2 \mathcal{L}_{\text{MI}} \quad (7)$$

4 Experiments

4.1 Experiment Setting

Dataset. We leverage the preprocessed dataset released by Aharoni and Goldberg (2020) consisting of five domains (IT, Koran, Law, Medical, Subtitles) available in OPUS (Tiedemann, 2012; Aulamo and Tiedemann, 2019). More details on the dataset and preprocessing are described in Appendix A.

Baseline. We compare our method with the following baseline models: (1) **Mixed** trains a model on all domains with uniform distribution, (2) **Domain-Tag** (Kobus et al., 2017) inserts domain information as an additional token in the input, (3) **Multitask Learning (MTL)** (Britz et al., 2017) trains a domain classifier simultaneously and encourage the sentence embedding to encompass its domain characteristics, (4) **Adversarial Learning (AdvL)** (Britz et al., 2017) makes the the sentence embedding to be domain-agnostic by flipping the gradient from the domain classifier before the back-propagation, (5) **Word-Level Domain Context Discrimination (WDC)** (Zeng et al., 2018) integrates two sentence embedding which are trained by MTL and AdvL respectively, (6) **Word-Adaptive Domain Mixing**[1] (Jiang et al., 2020), has domain-specific attention heads and the final representation is the combination of each head output based on the predicted domain proportion, and (7) **Domain-Adapter** (Pham et al., 2021) has separate domain adapters (Houlsby et al., 2019) and a source sentence passes through its domain adapters. This can be regarded as our model without general adapter and trained with $\mathcal{L}_{\text{DA}}$.

4.2 Main Results

Table 1 presents sacreBLEU (Post, 2018) and chrF (Popović, 2015) score from each model in all domains. For a fair comparison, we matched the number of parameters for all models. Baseline results following its original implementation with different parameter size are provided in Appendix C. Interestingly, Mixed performs on par with Domain-Tag and outperforms Word-Adaptive Domain Mixing, suggesting that not all multi-domain NMT methods are effective. Although adapter-based models (*i.e.*, Ours (w/o $\mathcal{L}_{\text{MI}}$) and Domain-Adapter) outperform Mixed, the performance increase is still marginal. Our model has gained 1.15 BLEU improvement over Mixed. It also outperforms all baselines with statistically significant difference.

As an ablation study of our MI objective, we conduct experiments without $\mathcal{L}_{\text{MI}}$ to prove its effectiveness. The result confirms that $\mathcal{L}_{\text{MI}}$ encouraged the model to learn domain specific knowledge leading to refined translation.

4.3 Mutual Information Distribution

We visualize XMI(i) in Eq. (3) to verify that our proposed loss penalizes low XMI. Figure 2 is the histogram of XMI(i) from the test samples in Law. Other domain distributions are in Appendix D. We use Domain-Adapter for comparison since it performs the best among the baselines. For p_G, we use the output probability of Mixed for both cases. From the distributions, our method indeed penal-

[1]We conducted experiments using publicly available code.

	IT	Koran	Law	Medical	Subtitles	Average
Mixed	43.87±0.505	20.31±0.371	58.33±0.474	55.19±0.737	30.36±0.424	41.61
	62.00±0.403	41.75±0.343	73.41±0.303	69.14±0.346	45.73±0.424	58.40
Domain-Tag	44.29±0.142	20.44±0.236	58.47±0.275	55.39±0.288	30.61±0.220	41.84
	62.30±0.111	41.75±0.203	73.56±0.190	69.28±0.160	45.99±0.268	58.58
MTL	44.00±0.298	20.40±0.198	58.27±0.327	55.24±0.564	30.52±0.478	41.69
	62.11±0.169	41.78±0.174	73.42±0.197	69.16±0.235	45.87±0.316	58.47
AdvL	43.86±0.167	20.33±0.275	58.40±0.195	55.56±0.245	30.43±0.367	41.71
	61.91±0.099	41.79±0.206	73.42±0.193	69.30±0.184	45.80±0.208	58.44
WDC	44.44±0.193	20.75±0.212	58.49±0.193	55.43±0.308	30.52±0.242	41.93
	62.27±0.175	42.05±0.198	73.58±0.182	69.20±0.203	45.87±0.125	58.59
Word-Adaptive	41.88±0.240	19.84±0.297	55.82±0.594	52.88±0.785	30.39±0.141	40.16
Domain Mixing	60.37±0.113	41.02±0.212	71.79±0.290	67.62±0.396	45.63±0.113	57.29
Domain-Adapter	44.50±0.342	20.37±0.193	58.22±0.169	56.00±0.243	31.02±0.334	42.02
	62.30±0.248	41.65±0.160	73.40±0.066	69.54±0.149	46.30±0.306	58.64
Ours (w/o $\mathcal{L}_{\text{MI}}$)	44.65±0.318	20.43±0.286	58.21±0.692	55.38±0.684	30.82±0.498	41.90
	62.49±0.221	41.77±0.262	73.40±0.416	69.28±0.377	46.16±0.414	58.62
Ours	**45.89**±0.215 **(+1.39)**	**20.80**±0.298 **(+0.43)**	**59.22**±0.306 **(+1.00)**	**56.34**±0.238 **(+0.34)**	**31.56**±0.218 **(+0.54)**	**42.76 (+0.74)**
	63.19±0.204 **(+0.89)**	**42.05**±0.274 **(+0.39)**	**74.02**±0.219 **(+0.62)**	**69.94**±0.238 **(+0.40)**	**46.46**±0.261 **(+0.16)**	**59.13 (+0.49)**

Table 1: Average and standard deviation of BLEU (upper line) and chrF (bottom line) from five random seed experiments. Bold indicates the best performance within a domain. Our model outperforms all baselines with significant margins ($p < 0.05$).

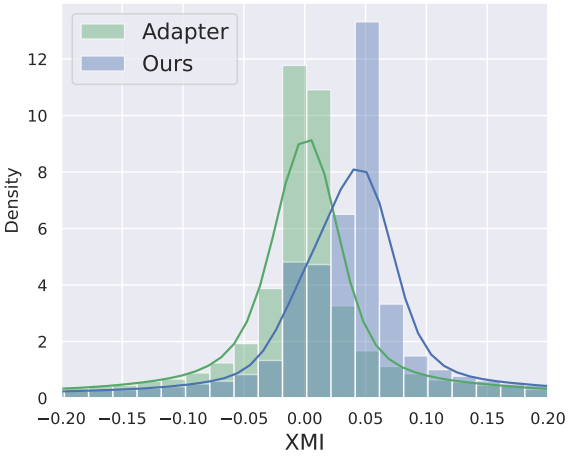

Figure 2: XMI distribution in Law. X-axis is XMI and Y-axis is the density. Green is Domain-Adapter and blue is our model. Our model has more high XMI values.

	-Q1	Q1-Q2	Q2-Q3	Q3-Q4	Average
IT	2.26	1.14	1.12	1.27	1.39
Koran	0.97	0.65	0.49	0.41	0.43
Law	0.75	0.73	1.41	1.17	1.00
Medical	0.25	0.08	0.60	0.40	0.34
Subtitles	0.36	0.83	0.83	2.10	0.54

Table 2: BLEU improvements in each quartiles. Q1, Q2, Q3 and Q4 represents 25%, 50%, 75% 100% respectively. The higher the quartile, the more domain specific the samples.

izes low XMI and encourages the model to have high XMI in all domains.

4.4 Translation Performance for Domain Specialized Sentences

Since the ultimate goal is to specialize multi-domain NMT, we calculate BLEU score improvement according to the domain specificity. We extract top 1% TF-IDF words in train source sentences in each domain (examples are in Appendix E) and consider them as domain-specific keywords. We assume that the more these keywords are included in the source sentence, the more domain specialized the sample is. We divide the test set into quartiles based on the number of the keywords the source sentence contains.

Table 2 reports BLEU score improvement compared to Domain-Adapter in each quartile along with averaged performance increases. In Law, Medical and Subtitles, BLEU score improvement increases as quartile gets higher. Furthermore, the improvements in Q2-Q3 and Q3-Q4 are larger than the averaged improvement score (*i.e.*, Average column). However, in IT and Koran, -Q1 has the largest performance increases. We conjecture the reason is that in both domains, the number of

	Finance	Ordinance	Tech	Average
Mixed	52.50±0.220	56.65±0.100	66.00±0.242	58.38
	72.64±0.105	75.36±0.091	81.60±0.121	76.53
Domain-Tag	52.71±0.231	56.60±0.115	66.03±0.360	58.45
	72.77±0.175	75.38±0.058	81.64±0.185	76.60
WDC	52.75±0.136	56.56±0.124	65.93±0.214	58.41
	72.78±0.135	75.34±0.053	81.53±0.099	76.55
Domain-Adapter	53.13±0.186	56.97±0.129	66.25±0.103	58.78
	72.98±0.170	75.48±0.066	81.76±0.079	76.74
Ours	**53.87**±0.188	**57.47**±0.086	**66.66**±0.191	**59.33**
	(+0.74)	**(+0.50)**	**(+0.41)**	**(+0.55)**
	73.41±0.162	**75.81**±0.033	**81.99**±0153	**77.07**
	(+0.43)	**(+0.33)**	**(+0.23)**	**(+0.33)**

Table 3: Average and standard deviation of BLEU (upper line) and chrF (bottom line) from five random seeds on Ko-En dataset. Bold indicates the best performance within a domain.

top TF-IDF words include in higher quartiles is fewer than the other domains. This weak distinction among quartiles in IT and Koran can be the root cause of marginal performance improvement. Details on number of captured keywords are in Appendix E.

4.5 Experiment Results on Korean-English

To verify the effectiveness of our proposed method in different language, we additionally conducted experiment on Korean-English dataset which has approximately 1M samples with three domains: Finance, Ordinance and Tech. The dataset is obtained from AIhub[2] which is publicly available. Model configuration is identical with the main experiment on OPUS. More experimental details are in Appendix A.

Table 3 demonstrates the results from the major baselines and our model, where we select top-4 baselines in the experiment on OPUS (Table 1). Our model achieves the best performance in all three domains, outperforming Domain-Adpater by 0.55 BLEU score on average. This result confirms that our proposed method can be further extended to other languages.

4.6 Samples with MI Visualization

Figure 3 demonstrates test set outputs with MI values generated by our model. Color intensity is correlated with MI value; the more intense the red, the more higher MI value. Note that the model has high MI especially when generate domain-specific words (*e.g.*, 'password' in IT and 'omalizumab' in Medical). This result is analogous to our motivation

[2]https://aihub.or.kr/

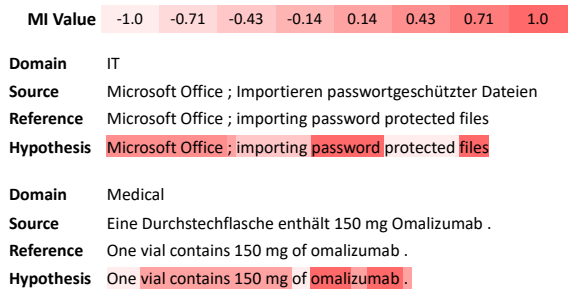

Figure 3: Example visualizations with MI values from IT and Medical. The more intense the red, the more higher MI value.

	Domain-Adapter	Ours
Number of Iterations (↓)	51.7K	48.5K
Peak Memory (GB) (↓)	26.79	27.09
Words per Second (↑)	22.9K	22K
Updates per Second (↑)	0.4	0.38

Table 4: Comparison of training computation cost between Domain-Adapter and Ours. The values are averaged across five seed experiments.

in that high MI value encourages model to translate domain peculiar terms. More samples are provided in Appendix F.

4.7 Computation Cost for Training

We compare computation cost between Domain-Adapter and our proposed model. Domain-Adapter was chosen because it shares the same model architecture with ours. Table 4 provides four computation cost during training: Number of Iterations until converge, Peak Memory, Words per Second, and Updates per Second. Our model requires fewer number of iterations needed to be trained (3.2K difference on average across five seeds). Our model has slightly higher peak memory (0.3GB, 0.94%) than Domain-Adapter, however, we believe this is acceptable when considering the performance improvement. Furthermore, there was not much difference in words per second and updates per second during training.

5 Conclusion

We build a specialized multi-domain NMT by adding MI-based loss. We reinterpret domain-specific knowledge from MI perspective and promote a model to explore domain knowledge by penalizing low MI. Our results prove that the proposed method is effective in increasing overall MI.

Limitations

Although many previous multi-domain NMT studies regard the source of the given sentence as its domain, equating domain and corpora is a naive approach and can partially represent the data. (Aharoni and Goldberg, 2020) For instance, some sentences may incorporate multiple domain characteristics or can be better translated under different domain other than its source domain. (Currey et al., 2020; Pham et al., 2021) This problem is not limited to our work but is applicable to other previous multi-domain NMT studies. Establishing a more proper definition of domain is a future work and a critical challenge in multi-domain NMT.

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A Experiment Settings

A.1 Dataset

For preprocessing, we conducted tokenization and normalize-punctuation by using Moses (Koehn et al., 2007) pipeline. We additionally eliminated samples with (i) sequences shorter than one subword-token, (ii) sequences longer than 250 subword-tokens, (iii) severe length imbalance between the language pair (top, bottom 5% for each domain) for both De-En and Ko-En. Table 5 and 6 show the final number of samples.

De-En	Train	Dev	Test
IT	211,374	1,888	2,000
Koran	16,952	1,872	2,000
Law	434,555	1,861	2,000
Medical	233,167	1,873	2,000
Subtitles	470,611	1,899	2,000

Table 5: Number of samples in De-En

Ko-En	Train	Dev	Test
Finance	156,569	9,510	5,000
Ordinance	79,802	9,335	5,000
Tech	711,885	9,251	5,000

Table 6: Number of samples in Ko-En

A.2 Experiment Details

For De-En, we use a joint BPE vocabulary (Sennrich et al., 2016) learned with 32k merge operations. For Ko-En, we train BPE vocabulary with 32k size separately for each language since Korean and English do not share characters. Remainig experiment settings are identical for both language pairs. Our experiments are conducted under open-source fairseq[3] (Ott et al., 2019) framework. We built upon Transformer model (Vaswani et al., 2017) which has 6 encoder and decoder layers with embedding dimension of 512, feed-forward dimension of 2048, and attention heads of 8. Parameters of encoder embedding, decoder embedding and decoder last layer are shared. We also utilize the same sinusoidal positional embedding following the original work. We fix dropout to 0.1 and used ReLU (Agarap, 2018) as an activation function. Following Bapna et al. (2019), the domain and general adapters ($\phi_1, \cdots \phi_N, \phi_G$) are inserted after feed-forward layer following the multi-head attention. Note that our training differs in that we jointly train all parameters from scratch including adapters on all domains.

The bottleneck size of the adapters is 256. Adapters are initialized from zero-mean Gaussian with standard deviation 10^{-2} which proven to be most effective in the proposed work. We searched the best combination of λ_1 and λ_2 by grid search ranging from 0.5 to 1.0. Then, we set λ_1 and λ_2 both to 1. All experiments are trained with label-smoothing cross-entropy loss with smoothing parameter of 0.1. All experiments are conducted using 8 NVIDIA V100 GPU.

In all experiments, a model is trained until early stopping with patience of 10 based on BLEU. We use Adam (Kingma and Ba, 2014) optimizer with an initial learning rate of $5{\cdot}e^{-4}$, where the learning rate is searced within the range of 0.001 to 0.0001. The tokens per batch is 8192 in all experiments. We compute sacreBLEU score [4] from outputs using beam search with a beam size of 5.

A.3 Baselines

In this section, we provide a detailed explanation on each baseline. Mixed and Domain-Tag employ identical model architecture with our model excluding adapters. Mixed does not utilize domain information and treat all samples are from identical distribution. On the other hand, Domain-Tag distinguishes domain by adding domain tag in front of the input sentence. We enlarged Mixed and Domain-Tag to Mixed-Big and Domain-Tag-big by increasing encoder and decoder embedding dimension to 608.

For Word-Adaptive Domain Mixing, we borrowed publicly available code and applied on our dataset. We applied word-adaptive training in both encoder and decoder because it had the best performance in the original paper. Other configurations are the same with ours.

Domain-Adapter has the domain-specific adapters $\phi_1, \cdots, \phi_N$, and the input sentence passes through only its domain adapter. Note that there are two major differences between Domain-Adapter and ours. First, Domain-Adapter does not need general adapter ϕ_G since it does not calculate $p_G(Y|X)$. Second, a source sentence

[3] https://github.com/facebookresearch/fairseq

[4] sacreBLEU signature: BLEU+c.mixed+l.de-en+#.1+s.exp+tok.13a+v.2.0.0

only passes through the model once only through its domain adapter ϕ_d. Similar to our method, all the parameters including adapters are jointly trained from scratch.

B Full Derivation of Domain-Aware Mutual Information

Below is the full derivation of Domain-Aware Mutual Information.

$$
\begin{aligned}
MI(D;Y|X) &= \mathbb{E}_{D,X,Y}\left[\log \frac{p(D,Y|X)}{p(D|X)\cdot p(Y|X)}\right] \\
&= \mathbb{E}_{D,X,Y}\left[\log \frac{p(D|Y,X)\cdot \cancel{p(Y|X)}}{p(D|X)\cdot \cancel{p(Y|X)}}\right] \\
&= \mathbb{E}_{D,X,Y}\left[\log \frac{p(X,Y,D)\cdot p(X)}{p(X,Y)\cdot p(X,D)}\right] \\
&= \mathbb{E}_{D,X,Y}\left[\log \frac{p(Y|X,D)}{p(Y|X)}\right]
\end{aligned}
$$

The proof from the first to the second line is provided below.

$$
\begin{aligned}
&P(X,Y,D) = P(D|Y,X)\cdot P(Y|X)\cdot P(X) \\
\Rightarrow\ &P(D,Y|X) = P(D|Y,X)\cdot P(Y|X)
\end{aligned}
$$

C Additional Baseline Results

Table 7 shows sacreBLEU (Post, 2018) and chrF (Popović, 2015) score from baseline models (Mixed-Small, Domain-Tag-Small, Word-Adaptive Domain Mixing Big) following its original implementation with different number of parameters. Note that Mixed and Domain-Tag underperform the models in the main experiment, and Word-Adaptive Domain Mixing becomes effective when enlarge model size.

D MI Histogram

XMI histograms from all doamins are in Fig. 4. Adpater (baseline) is colored in green and our model is in blue. From the plot, we can verify that in all domains, our model outputs higher XMI compared to the baseline.

E Details on Translation Performance for Domain Specialized Experiment

Examples of extracted TF-IDF keywords are in Table 8. We removed stop words and conducted lemmatization before extracting keywords. As expected, chosen words are correlated to its domain are chosen.

Averaged number of captured keywords in each quartile is presented in Table 9. Compared to Law, Medical and Subtitles where a clear distinction among quartiles by the averaged number of keywords exists, IT and Koran have a minimal change indicating a weak distinction.

F Samples with MI Visualization

Figure 5 provides more visualizations of test examples with MI values from IT, Law, and Medical. Color intensity is correlated with MI value; the more intense the red, the more higher MI value. From the result, domain-specific words (*e.g.*, 'account' in IT, 'Regulation' in Law, 'pharmacokinetic' in Medical) are translated with high MI values.

	# of Parameters	IT	Koran	Law	Medical	Subtitles	Average
Mixed-Small	60M	43.64±0.253 61.96±0.204	20.74±0.155 42.01±0.159	57.47±0.376 72.95±0.275	54.88±0.553 68.98±0.362	30.58±0.273 46.06±0.293	41.46 58.39
Mixed	76M	43.87±0.505 62.00±0.403	20.31±0.371 41.75±0.343	58.33±0.474 73.41±0.303	55.19±0.737 69.14±0.346	30.36±0.424 45.73±0.424	41.61 58.40
Domain-Tag-Small	60M	44.00±0.409 62.09±0.242	20.39±0.251 41.71±0.141	57.80±0.206 73.14±0.183	54.91±0.197 68.97±0.056	31.10±0.316 46.34±0.208	41.64 58.45
Domain-Tag	76M	44.29±0.142 62.30±0.111	20.44±0.236 41.75±0.203	58.47±0.275 73.56±0.190	55.39±0.288 69.28±0.160	30.61±0.220 45.99±0.268	41.84 58.58
MTL	76M	44.00±0.298 62.11±0.169	20.40±0.198 41.78±0.174	58.27±0.327 73.42±0.197	55.24±0.564 69.16±0.235	30.52±0.478 45.87±0.316	41.69 58.47
AdvL	76M	43.86±0.167 61.91±0.099	20.33±0.275 41.79±0.206	58.40±0.195 73.42±0.193	55.56±0.245 69.30±0.184	30.43±0.367 45.80±0.208	41.71 58.44
WDC	76M	44.44±0.193 62.27±0.175	20.75±0.212 42.05±0.198	58.49±0.193 73.58±0.182	55.43±0.308 69.20±0.203	30.52±0.242 45.87±0.125	41.93 58.59
Word-Adaptive Domain Mixing Big	218M	44.08±0.561 61.93±0.273	20.34±0.257 41.23±0.334	59.63±0.308 74.26±0.196	56.81±0.386 69.96±0.245	29.34±0.488 44.62±0.460	42.04 58.40
Word-Adaptive Domain Mixing	76M	41.88±0.240 60.37±0.113	19.84±0.297 41.02±0.212	55.82±0.594 71.79±0.290	52.88±0.785 67.62±0.396	30.39±0.141 45.63±0.113	40.16 57.29
Domain-Adapter	76M	44.50±0.342 62.30±0.248	20.37±0.193 41.65±0.160	58.22±0.169 73.40±0.066	56.00±0.243 69.54±0.149	31.02±0.334 46.30±0.306	42.02 58.64
Ours (w/o $\mathcal{L}_{\text{MI}}$)	76M	44.65±0.318 62.49±0.221	20.43±0.286 41.77±0.262	58.21±0.692 73.40±0.416	55.38±0.684 69.28±0.377	30.82±0.498 46.16±0.414	41.90 58.62
Ours	76M	**45.89**±0.215 **(+1.39)** **63.19**±0.204 **(+0.89)**	**20.80**±0.298 **(+0.43)** **42.05**±0.274 **(+0.39)**	**59.22**±0.306 **(+1.00)** **74.02**±0.219 **(+0.62)**	**56.34**±0.238 **(+0.34)** **69.94**±0.238 **(+0.40)**	**31.56**±0.218 **(+0.54)** **46.46**±0.261 **(+0.16)**	**42.76** **(+0.74)** **59.13** **(+0.49)**

Table 7: Average and standard deviation of BLEU (upper line) and chrF (bottom line) from baselines with different parameter size and our model.

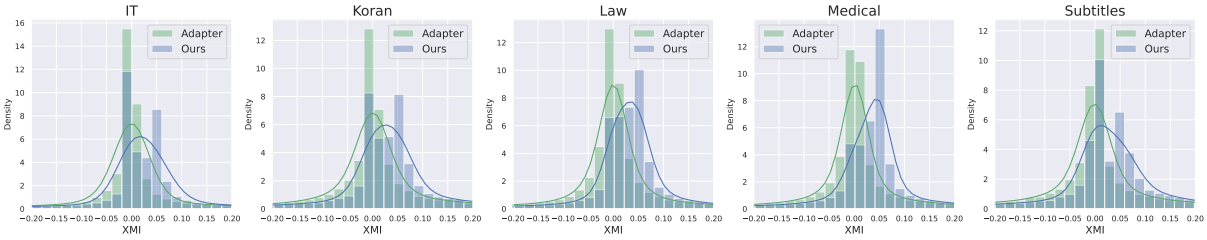


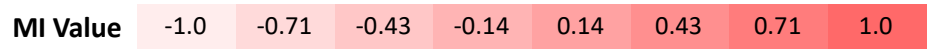
Figure 4: XMI distributions from all domains. X-axis is XMI and Y-axis is the density. Adpater is colored in green and our model is in blue. Our XMI distribution has more higher values than baseline.

	Examples of TF-IDF Keywords
IT	übertragungsrate (transfer rate), zwischensumme (temporally save), YouTube, übertragungsfortschritt (transfer progress), speichergröße (memory size), yahoomail, zusammensetzungswerkzeug (composition tool), übersichtsmodus (overview mode), webserver, zwischengespeichert (cached), übersetzungsprogramm (translation game), zwischenablagename (clipboard name)
Koran	übertreter (transgressor), zwingherr (tyrant), widmest (dedicate), unterwürfig (submissive), unterworfen (subjected), städte (cities), sterben (die), schutzherr (patron), religion, muslime (muslims)
Law	überwachungszollstelle (supervising customs office), änderungsverfahren (change procedure), zustellungsmängel (delivery defects), wirtschaftsjahre (fiscal years), überstunden (overtime), zuschusssatz (subsidy rate), widerklänge (echoes), übernahmeprotokoll (takeover protocol), zulassungsvoraussetzungen (admission requirements), verwaltungskommission (administrative commission), tarife (rates)
Medical	überlebenswahrscheinlichkeit (probability of survival), verletzung (injury), tagesgesamtdosis (total daily dose), überempfindlichkeitsreaktionen (hypersensitivity reactions), zäpfchen (suppository), tremor, zytotoxisch (cytotoxic), urin (urine), Schatzungen (estimates), wirkstoffmatrix (active ingredient matrix), vorsichtsmaßnahmen (precautions)
Subtitles	übungen (exercises) , wähle (choose), übersehen (overlook), öffentlichkeitsarbeit (public relation), äußern (to express), ärger (trouble), ältester (oldest), zähflüssig (viscous), zwischenmahlzeiten (snacks), wäsche (laundry), werbepause (commercial break)

Table 8: Examples of TF-IDF extracted words of the source language (i.e., German). We randomly sampled 11 words from each domain among the top 1% keywords. We also write its meaning in english words in the bracket.

	IT	Koran	Law	Medical	Subtitles
-Q1	0	0	1.91	0.96	1.70
Q1-Q2	1	1	5.07	4.05	3.57
Q2-Q3	2	2	8.36	6.83	5.42
Q3-Q4	4.10	3.42	13.21	11.50	8.11

Table 9: Averaged number of captured top TF-IDF keywords in each quartile.



Domain: IT

Source Möchten Sie diesen Zugang wirklich löschen ?
Reference Do you really want to delete this account ?
Hypothesis Do you really want to delete this account ?

Source Datei , die eine Liste zu druckender Schriftarten enthält
Reference File containing list of fonts to print
Hypothesis File containing a list of fonts to print

Source Geben Sie IP @-@ Adresse und Port des Servers ein :
Reference Enter server IP address and port :
Hypothesis Enter IP address and port of the server :

Domain: Law

Source Der Wortlaut der Schreiben ist dieser Verordnung beigefügt .
Reference The text of the letters is annexed to this Regulation .
Hypothesis The text of the letters is attached to this Regulation .

Source Inkrafttreten , Änderung und Kündigung des Abkommens
Reference Entry into force , amendments to and termination of the Agreement
Hypothesis Entry into force , amendment and termination of the Agreement

Source Im Namen der Gemeinschaft Für die Republik Bulgarien
Reference On behalf of the Community For the Republic of Bulgaria
Hypothesis On behalf of the Community For the Republic of Bulgaria

Domain: Medical

Source Stabilität der rekonstituierten Suspension im Infusionsbeutel :
Reference Stability of the reconstituted suspension in the infusion bag :
Hypothesis Stability of the reconstituted suspension in the infusion bag :

Source Jede Durchstechflasche enthält 10 mg Basiliximab * .
Reference Each vial contains 10 mg basiliximab * .
Hypothesis Each vial contains 10 mg of basiliximab * .

Source Bei älteren Patienten wurden keine pharmakokinetischen Studien durchgeführt .
Reference Pharmacokinetic studies have not been performed in the elderly .
Hypothesis No pharmacokinetic studies have been performed in the elderly .

Figure 5: Visualization of examples with MI values from IT, Law, and Medical. Color intensity is correlated with MI value; the more intense the red, the more higher MI value.