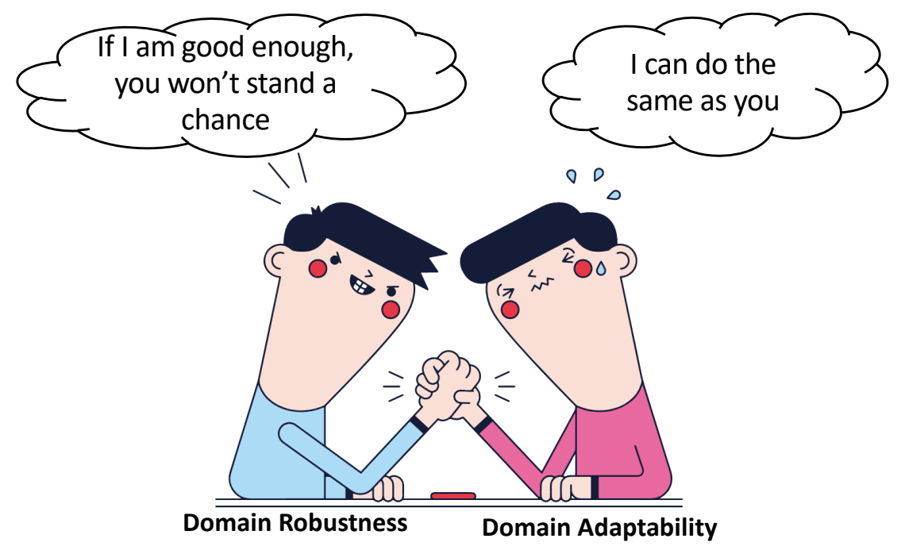
Improving Both Domain Robustness and Domain Adaptability in Machine Translation

Wen Lai[1], Jindřich Libovický[2] and Alexander Fraser[1]

[1] Center for Information and Language Processing, LMU Munich, Germany
[2] Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic
{lavine, fraser}@cis.lmu.de libovicky@ufal.mff.cuni.cz

Introduction



- We consider two problems of NMT domain adaptation using meta-learning:
  - **Domain Robustness**: we want to reach high quality on both domains seen in the training data and unseen domains.
  - **Domain Adaptability**: making it possible to finetune systems with just hundreds of in-domain parallel sentences.
- We propose a novel approach, **RMLNMT** (**R**obust **M**eta-**L**earning Framework for **N**eural **M**achine **T**ranslation Domain Adaptation), which improves the robustness of existing meta-learning models.

Method

Word-level Domain Mixing

- The domain of a word in the sentence is not necessarily consistent with the sentence domain. Therefore, we assume that every word in the vocabulary has a domain proportion, which indicates its domain preference.
- Each domain has its own multi-head attention modules. Therefore, we can integrate the domain proportion of each word into its multi-head attention module.
- Apply the domain mixing scheme in the same way for all attention layers and the fully-connected layers.
- The model can be efficiently trained by minimizing the composite loss:

$$L^* = L_{\text{gen}}(\theta) + L_{\text{mix}}(\theta)$$

Domain Classification

- Rieß et al. (2021) show that using scores from simple domain classifier are more effective than scores from language models for NMT domain adaptation.
- We compute domain similarity using a sentence-level classifier, but in contrast with previous work, we based our classifier on a pre-trained language model (BERT).

Online Meta-Learning

- We use domain classification scores as the curriculum to split the corpus into small tasks, so that the sentences more similar to the general domain sentences are selected in early tasks.
- Previous meta-learning approaches (Sharaf et al., 2020; Zhan et al., 2021) are based on token-size based sampling, which proved be not balanced since some tasks did not contain all seen domains, especially in the early tasks. To address these issues, we sample the data uniformly from the domains to compensate for imbalanced domain distributions based on domain classifier scores.
- Following the balanced sampling, the process of meta-training is to update the current model parameter from θ to θ' using a MAML (Finn et al., 2017) objective with the traditional sentence-level meta-learning loss $\mathcal{L}_{\mathcal{T}}(f_\theta)$ and the word-level loss $\Gamma_{\mathcal{T}}(f_\theta)$ (L^* of $\mathcal{T}$).

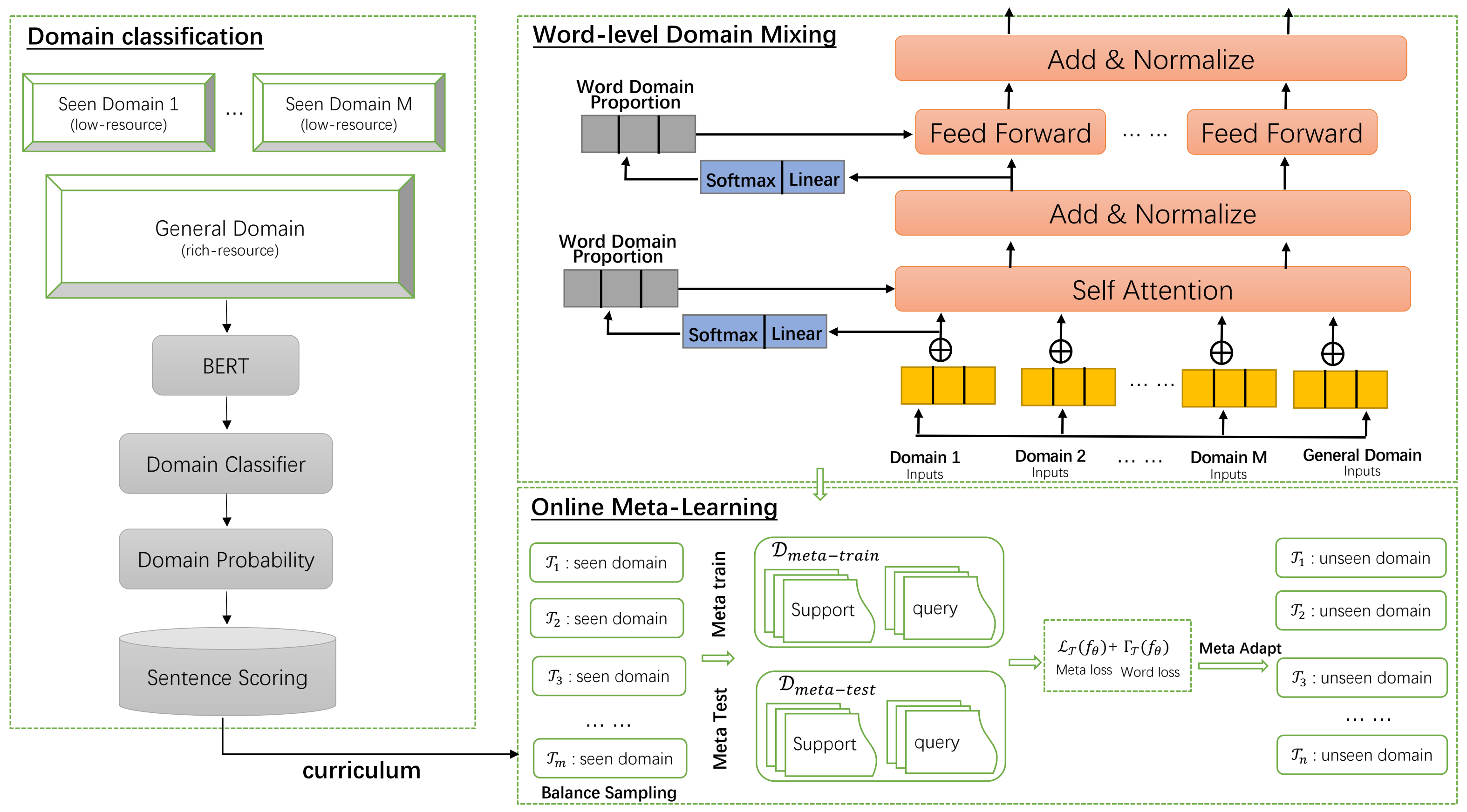


Figure 1: Method

Results

	Models	Unseen					Seen				
		Covid	Bible	Books	ECB	TED	EMEA	Globalvoices	JRC	KDE	WMT
1	Vanilla	24.34	**12.08**	12.61	29.96	27.89	37.27	24.19	39.84	27.75	27.38
2	Vanilla + tag	24.86	12.04	12.46	30.03	27.93	38.37	24.56	40.75	28.23	27.26
3	Meta-MT w/o FT	23.69	11.07	12.10	29.04	26.86	30.94	23.73	38.82	23.04	26.13
4	Meta-Curriculum (LM) w/o FT	23.70	11.16	12.24	28.22	27.21	33.49	24.27	39.21	27.60	25.83
5	RMLNMT w/o FT	**25.48**	11.48	**13.11**	**31.42**	**28.05**	**47.00**	**26.35**	**51.13**	**32.80**	**28.37**

Table 1: Domain Robustness

	Models	Unseen					Seen				
		Covid	Bible	Books	ECB	TED	EMEA	Globalvoices	JRC	KDE	WMT
1	Plain FT	24.81	12.61	12.78	30.48	28.36	37.26	24.26	40.02	27.99	27.31
2	Plain FT + tag	25.31	12.57	12.83	30.57	28.39	39.54	24.91	41.51	29.14	27.58
3	Meta-MT + FT	25.83	14.20	13.39	30.36	28.57	34.69	24.64	39.15	27.47	26.38
4	Meta-Curriculum (LM) + FT	**26.66**	14.37	13.70	30.41	28.97	34.00	24.72	39.61	27.37	26.68
5	RMLNMT + FT	26.53	**15.37**	**13.72**	**31.97**	**29.47**	**47.02**	**26.55**	**51.13**	**32.88**	**28.37**

Table 2: Domain Adaptability

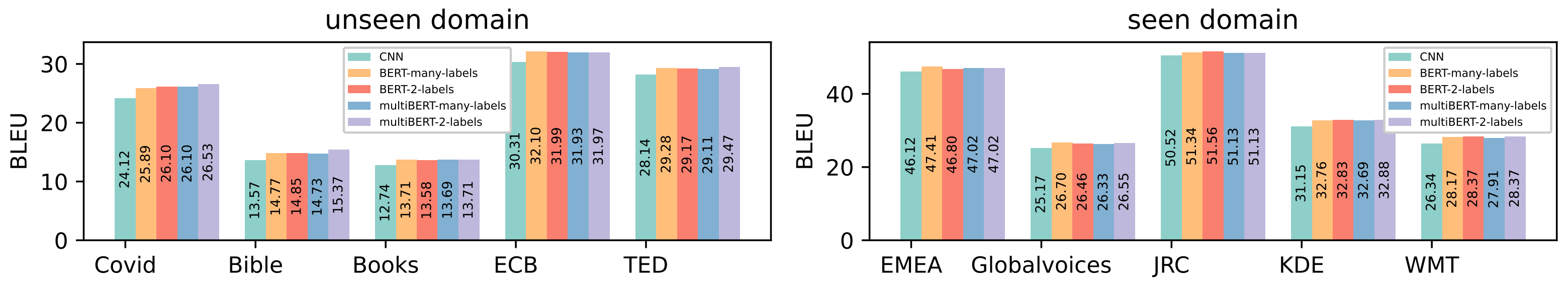


Figure 2: Different Clssifiers

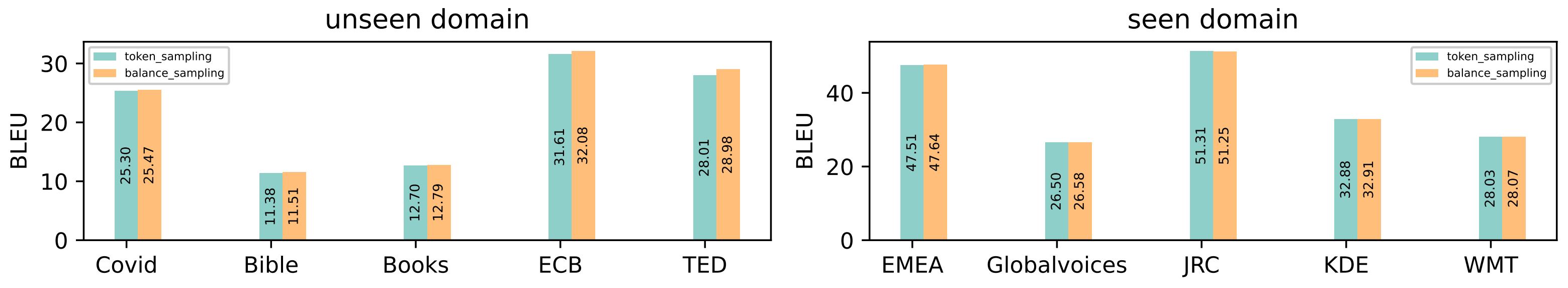


Figure 3: Different Sampling Strategy

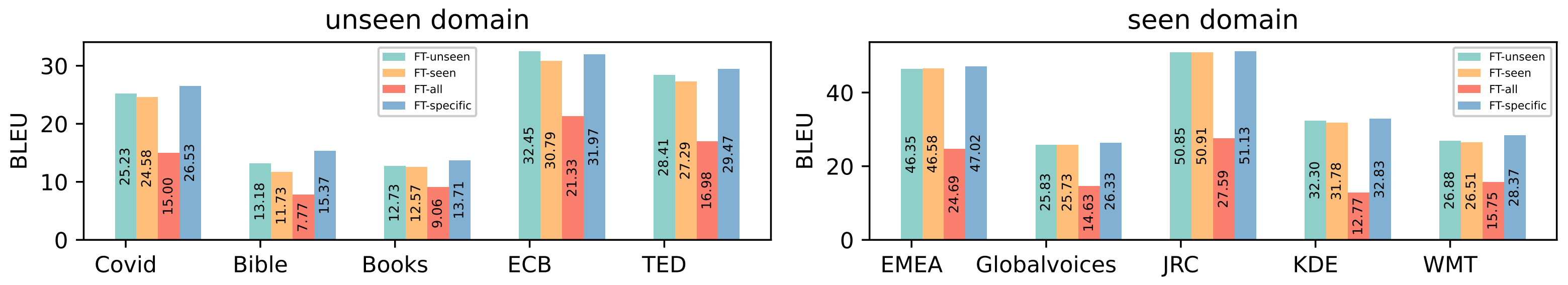


Figure 4: Different Fine-tuning Strategy

Learn More!

Code: https://github.com/lavine-lmu/RMLNMT **Blog**: https://lavine-lmu.github.io/lavine_blog

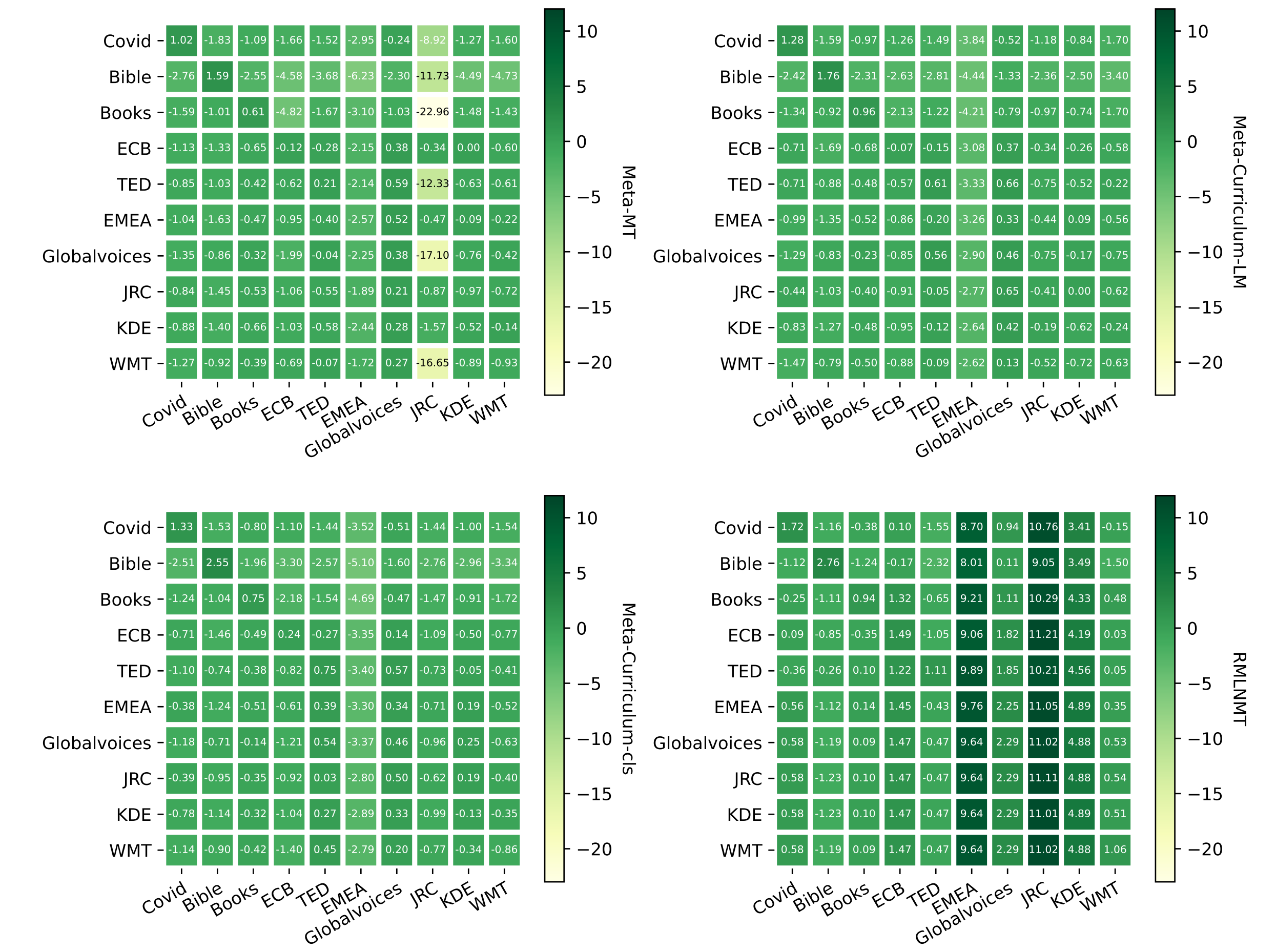


Figure 5: Cross-Domain Robustness

Analysis

- **Main Results**
  - **Domain Robustness**. Table 1 shows that RMLNMT got the best domain robustness both in seen and unseen domains.
  - **Domain Adaptability**. From Table 2, we observe that the traditional meta-learning approach shows high adaptability to unseen domains but fails on seen domains due to limited domain robustness. In contrast, RMLNMT shows its domain adaptability both in seen and unseen domains, and maintains the domain robustness simultaneously.
  - **Cross-Domain Robustness**. As shown in Figure 5, Compared with other methods, we observed that RMLNMT shows its robustness on all domains and that the model performance fine-tuned in one specific domain is not sacrificed in other domains.
- **Ablation Study**
  - **Different Classifiers**. In Figure 2, we observed that the performance of RMLNMT is not directly proportional to the accuracy of the classifier.
  - **Different Sampling Strategy**. Figure 3 shows that our methods can result in small improvements in performance.
  - **Different Fine-Tuning Strategy**. We observed on Figure 4 that fine-tuning in one specific domain obtains robust results among all the strategies.

Conclusion

- We presented RMLNMT, a robust meta-learning framework for low-resource NMT domain adaptation reaching both high domain adaptability and domain robustness (both in the seen domains and unseen domains).
- We found that domain robustness dominates the results compared to domain adaptability in meta-learning based approaches.

Acknowledgement

This work was supported by funding to Wen Lai's PhD research from LMU-CSC (China Scholarship Council) Scholarship Program. This work has received funding from the European Research Council under the European Union's Horizon 2020 research and innovation program (grant agreement #640550). This work was also supported by the DFG (grant FR $2829/4$-1). We thank Mengjie Zhao for the helpful comments.