Encoder-Aware Sequence-Level Knowledge Distillation for Low-Resource Neural Machine Translation

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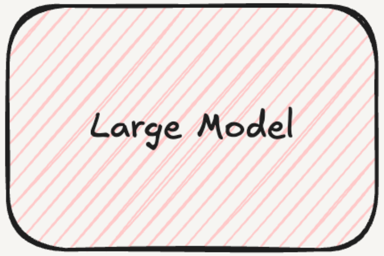
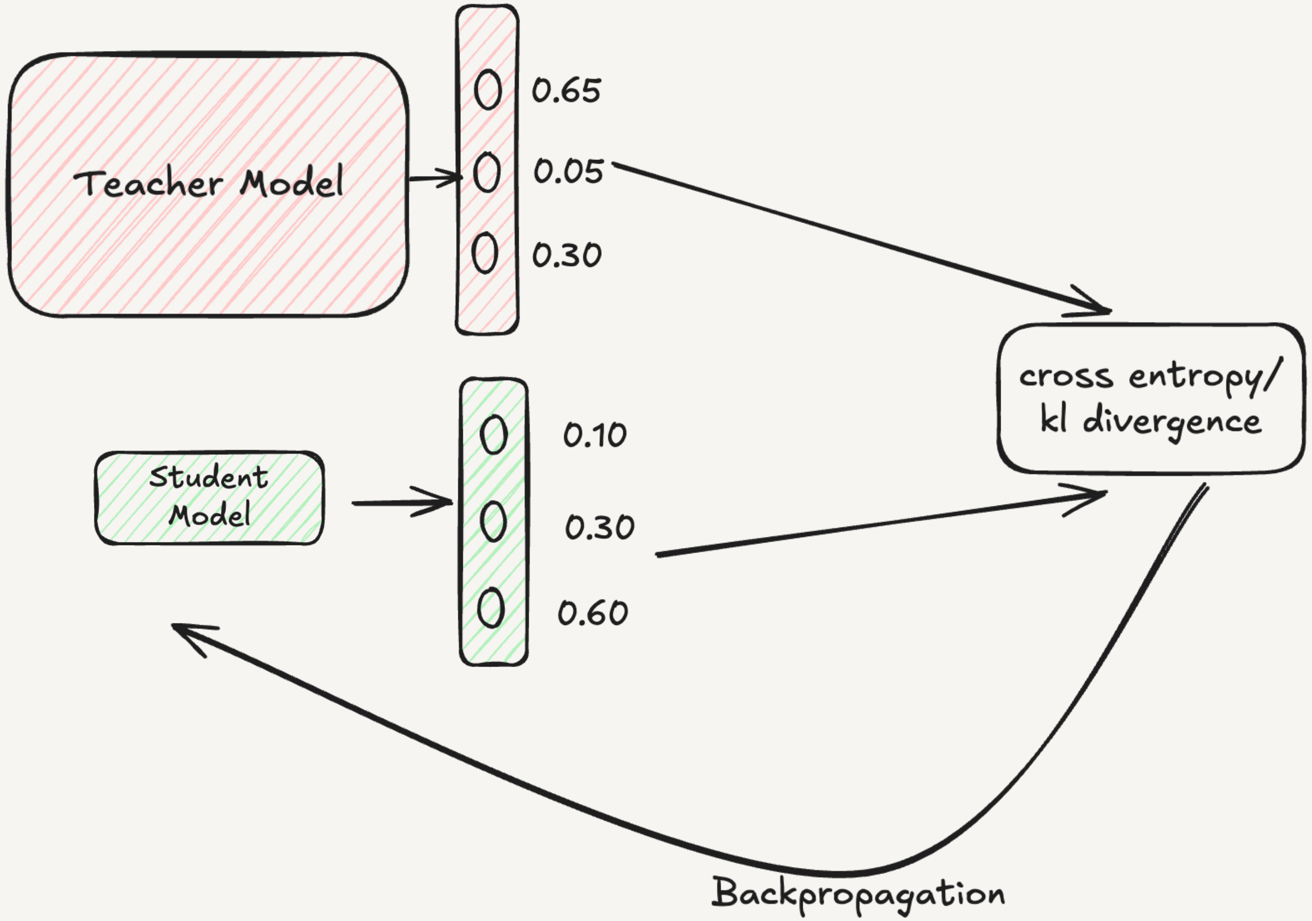
LoResMT@NAACL

Motivation

- Domain specific Neural Machine Translation (NMT) systems are of high demand as general NMT systems have limited applications (Saunders,2022).
- Sequence-Level Distillation (SLD) (Kim and Rush, 2016) enabled Knowledge Distillation (KD) (Hinton, 2015), to be applied for Sequence-to-Sequence (Seq2Seq) problem.
- Currey et al.(2020) utilized SLD to successfully perform multi-domain adaptation for NMT in high resource language setting.
- While LLMs excel in high-resource translation, encoder-decoder models outperform them in low-resource settings, making them still relevant and worth studying (Zhu et al., 2024).
- We hypothesize that SLD in encoder-decoder models **primarily distills the decoder**, resulting in limited encoder learning and weaker domain adaptation in low-resource settings; to address this, we introduce **encoder alignment to enhance knowledge transfer and adaptability**.

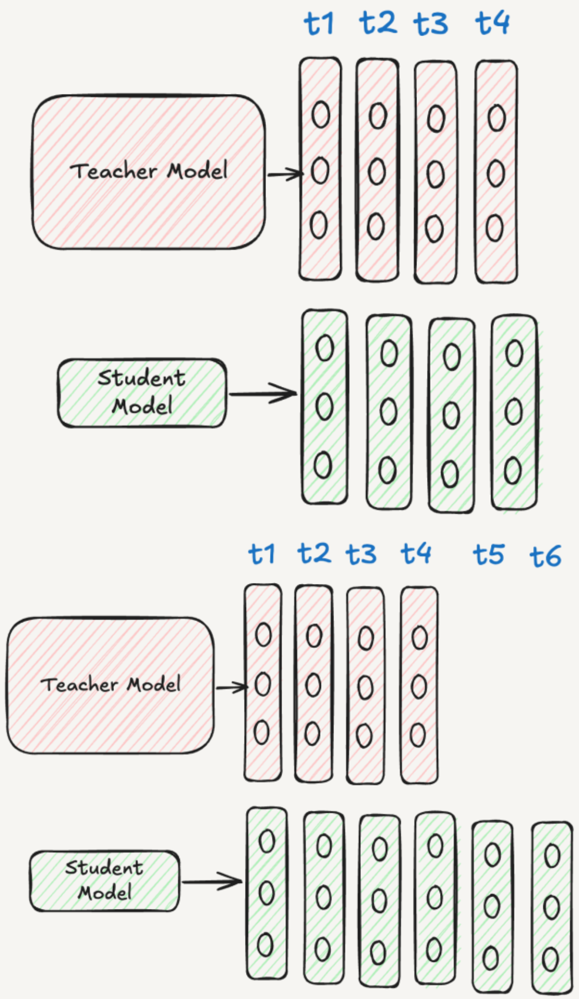
Knowledge Distillation

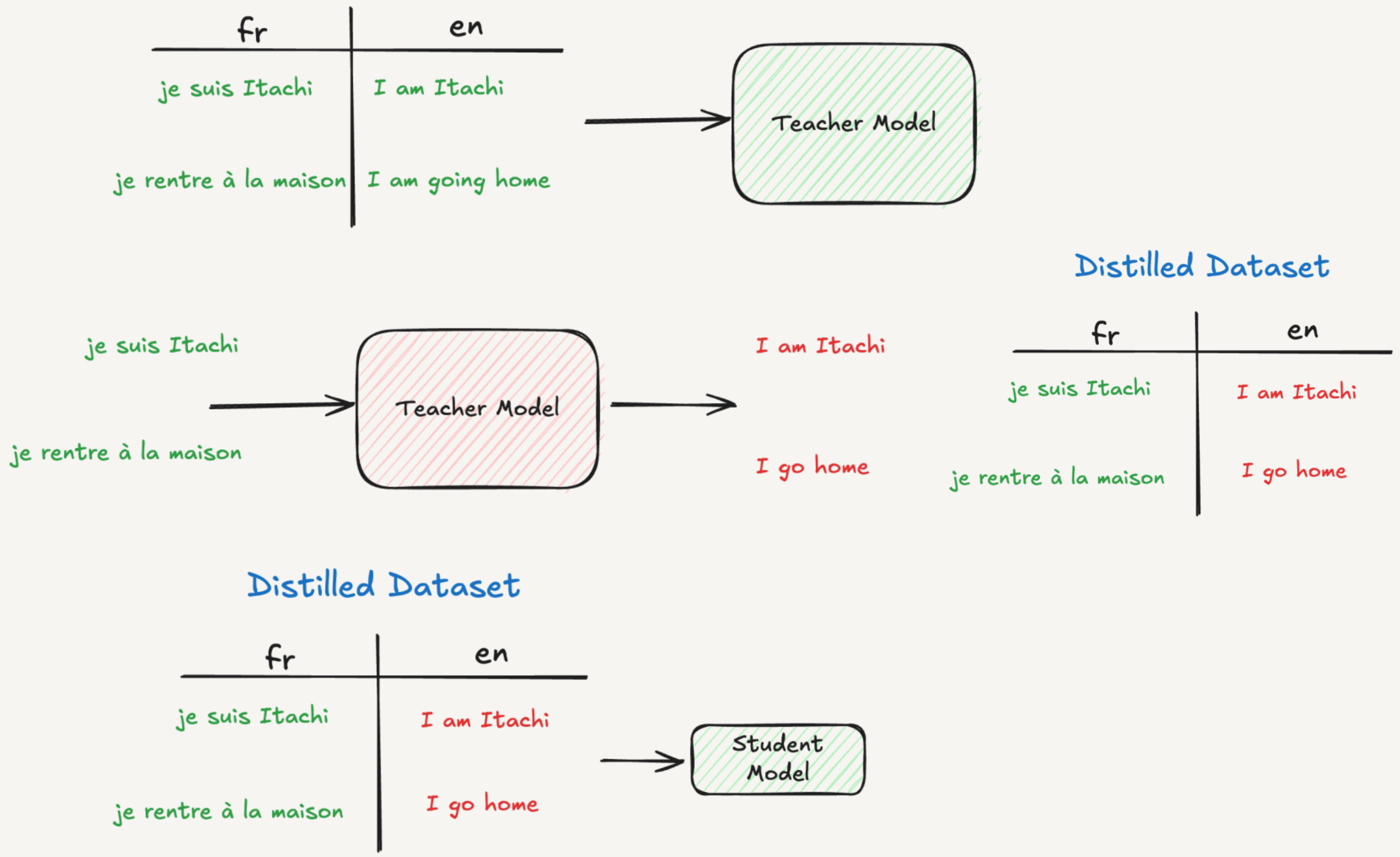




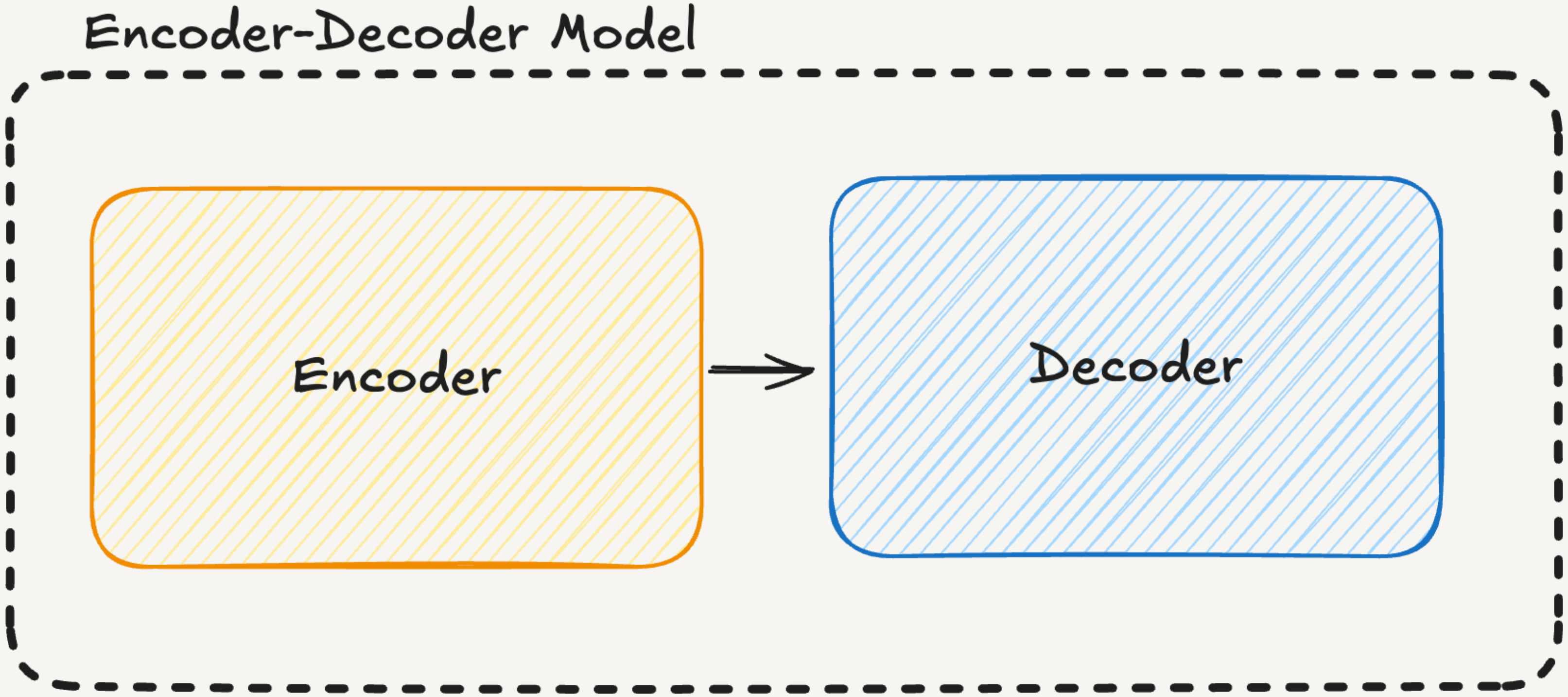
Sequence Level Distillation

Seq2Seq Task





Our Problem

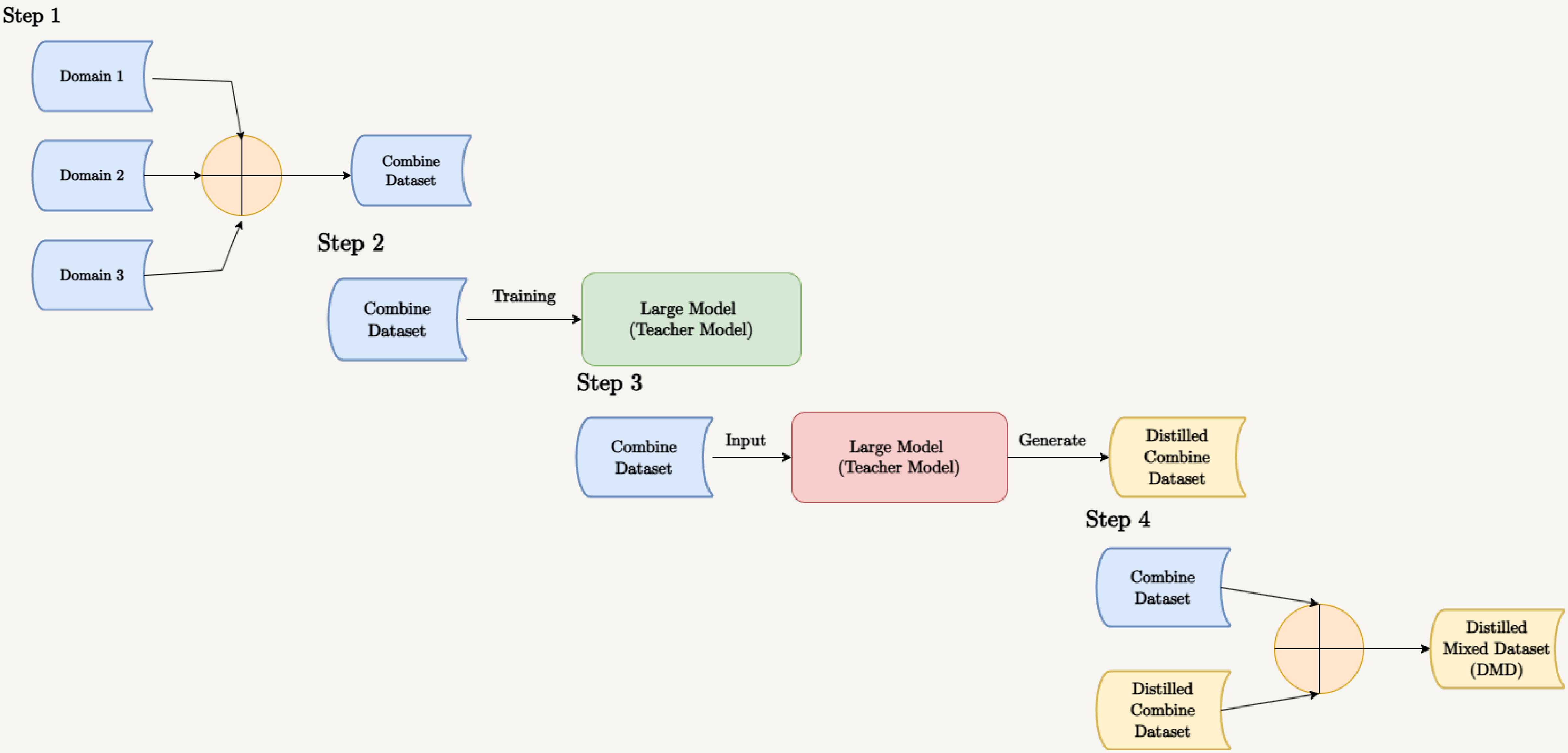


Research Questions

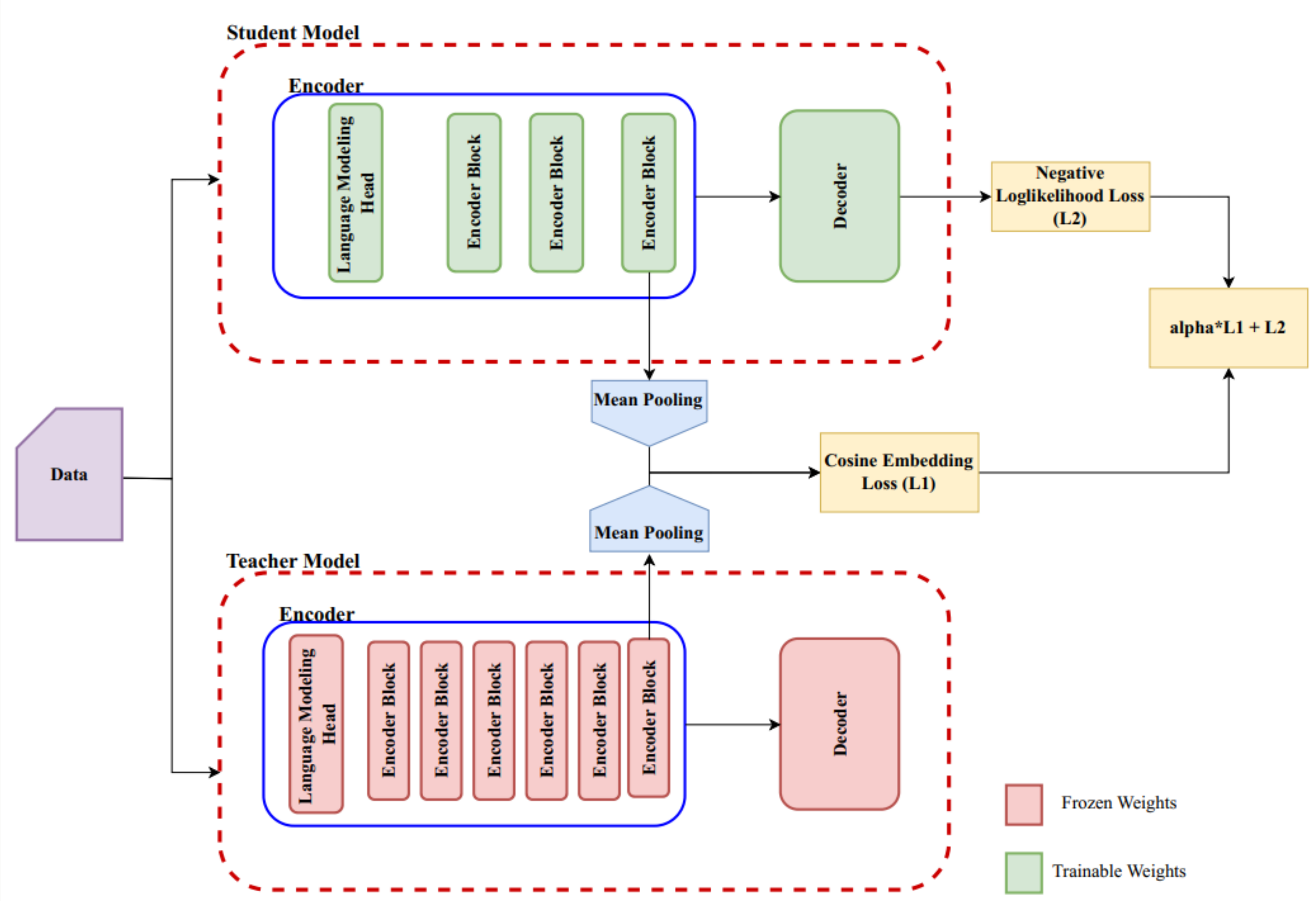
- **RQ1**: Is sequence-level knowledge distillation inherently decoder-focused in encoder-decoder NMT architectures?
- **RQ2**: Can encoder alignment improve knowledge transfer and domain adaptability in low-resource settings?

Methodology

Distilled Mixed Dataset(DMD) Creation



Proposed Teacher-Student Encoder Alignment



$$\mathrm{L}_{\mathrm{total}} = \alpha \cdot L_1 + L_2$$

- Here α is the attenuation factor used to control the contribution of the cosine embedding loss.
- We chose mean pooling based on BehnamGhader et al. (2024).
- A cosine-based loss function (Barz and Denzler,2019) was used for encoder alignment between teacher and student.

Experimental Setup

Two Studies

- **German-English**: simulated low resource setting, due to large number of domains (European Parliament, Law, Medical and News Commentary, Ted Talks, Open Subtitles).
- **Sinhala-English**: bonafide low resource setting.

German-English

- **Stage 1**: train on 4 domains (European Parliament, Law, Medical and News Commentary) and test on their respective test sets and one out of domain test set Flores200.
- **Stage 2**: further finetune the models from **Stage 1** on unseen domains (Ted talks, Open Subtitles).

Experimental Setup Contd.

Sinhala-English

- Study the impact of alpha.
- Train on 3 domains (CC Align, Open Subtitles, Sri Lankan Government) and test on their respective test sets and one out of domain test set Flores200.

Naming Conventions

- **L-ADO**: Large model trained on the All-Domain Original dataset.
- **S-ADO**: Small model trained on the All-Domain Original dataset.
- **S-ADD**: Small model trained on the All-Domain Distilled dataset (vanilla sequence-level distillation (Kim and Rush, 2016)).
- **S-DMD-NoAlign**: Small model trained on the Distilled Mixed Dataset (DMD) without teacher-student encoder alignment (as followed in (Currey et al., 2020)).
- **S-DMD-Align**: Small model trained on the DMD with teacher-student encoder alignment(using the proposed methodology).

Simulated Low Resource Setting (German-English)

Model	med	parl	law	news	Flores
L-ADO	63.27	56.33	63.73	53.80	50.89
S-ADO	62.31	55.66	62.39	53.28	50.23
S-ADD	62.36	56.08	62.92	53.87	50.90
S-DMD-NoAlign	61.38	55.49	61.89	52.91	49.88
S-DMD-Align	**63.43**	**56.92**	**64.08**	**54.88**	**52.90**

Table 2: ChrF scores of models trained with various configurations, evaluated on in-domain test sets (med, parl, law, news) and the out-of-domain Flores200 development-test set.

Model	opensub	ted
L-ADO	39.94	51.32
S-ADO	39.21	51.03
S-ADD	39.59	50.51
S-DMD-NoAlign	39.13	50.41
S-DMD-Align	**40.43**	**51.94**

Table 3: ChrF scores for Stage 1 models fine-tuned on single domains (Open Subtitles and Ted2020) to evaluate domain adaptation. Each model is fine-tuned on an individual domain and evaluated on its corresponding test set.

Real Low Resource Setting (English-Sinhala)

α	ccalign	opensub	gov	Flores
1.0	38.91	28.71	44.25	**28.11**
2.0	39.06	28.88	44.35	28.04
3.0	38.79	28.21	43.80	27.43
4.0	**39.54**	**28.91**	**44.66**	27.54
5.0	37.96	28.43	43.65	27.73
6.0	36.27	27.89	41.85	25.41
7.0	38.59	28.86	43.91	27.71

Table 4: ChrF scores of our model trained on the English–Sinhala language pair with different α values using the distilled dataset, evaluated on three in-domain test sets and the out-of-domain Flores200 development-test set.

Model	alpha	ccalign	opensub	gov	Flores
L-ADO	–	41.95	28.88	**48.44**	29.81
S-ADO	–	39.23	28.58	45.69	28.34
S-ADD	–	38.41	28.67	43.46	27.15
S-DMD-NoAlign	–	42.34	30.11	47.62	30.47
S-DMD-Align	1.0	42.78	30.36	47.25	30.54
S-DMD-Align	4.0	**43.11**	**30.42**	48.20	**31.03**

Table 5: ChrF scores of models trained with various configurations for the English–Sinhala translation direction, evaluated on three in-domain test sets and the out-of-domain Flores200 development-test set.

Conclusion

- RQ1 Answered: We confirmed that sequence-level distillation mainly transfers decoder knowledge, limiting encoder learning and leading to suboptimal performance.
- RQ2 Answered: Introducing encoder alignment improves knowledge transfer, resulting in better generalization and domain adaptability, especially in low-resource settings.
- Practical Impact: Our approach is effective even in compute-poor environments, making it a viable solution for multi-domain NMT under real-world constraints.

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Thank you!