A Appendix

A.1 Dataset

Table 6 summarizes the number of parallel sentences for 14 languages in WMT shared tasks. Table 7 covers three datasets, CoVoST 2, EuroParl and mTEDx on ASR task, and reports their number of utterances in 8 languages. Table 8 shows data sizes of three ST datasets including CoVoST 2, EuroParl and mTEDx. It reports the number of utterances in 13 language directions.

Table 6: Data Statistics of WMT Datasets

Language	Code	Size	Language	Code	Size
Gujarati	gu	10k	Kazakh	kk	91k
Turkish	tr	207k	Romanian	ro	608k
Estonian	et	1.94M	Lithuanian	lt	2.11M
Finnish	fi	2.66M	Latvian	lv	4.50M
Czech	cs	11M	Spanish	es	15M
Chinese	zh	25M	German	de	28M
Russian	ru	29M	French	fr	41M

Table 7: Data Statistics of Speech Recognition Task (# of Utterances)

Data	CoVoST 2			EuroParl			mTEDx		
Split	Train	Dev	Test	Train	Dev	Test	Train	Dev	Test
ar	2,283	1,758	1,695	-	-	-	11,442	1,079	1,066
de	127,577	13,503	13,503	13,099	2,653	2,644	6,659	1,172	1,126
el	-	-	-	-	-	-	12,521	982	1,027
es	78,958	13,203	13,204	7,537	1,951	1,831	99,660	905	1,012
fr	207,286	14,755	14,750	13,006	1,593	1,848	114,488	1,036	1,059
it	31,638	8,877	8,892	11,649	1,414	1,763	48,089	931	999
pt	9,158	3,315	4,021	4,977	1,794	2,292	88,123	1,013	1,020
ru	12,112	6,110	6,300	-	-	-	28,627	973	1,132

Table 8: Data Statistics of Speech Translation Task (# of Utterances)

Data	CoVoST 2			EuroParl			mTEDx		
Split	Train	Dev	Test	Train	Dev	Test	Train	Dev	Test
el-en	-	-	-	-	-	-	4,215	938	1,024
es-en	78,958	13,203	13,204	7,403	1,947	1,816	35,186	899	1,001
es-fr	-	-	-	4,673	1,115	1,082	3,549	904	1,005
es-it	-	-	-	4,476	1,065	1,079	5,530	16	262
es-pt	-	-	-	4,727	1,141	1,089	20,467	898	1,002
fr-en	207,286	15,560	14,952	12,446	1,481	1,804	29,634	1,035	1,058
fr-es	-	-	-	7,857	1,072	1,098	20,407	1,034	1,057
fr-pt	-	-	-	8,183	1,048	1,100	13,047	1,035	1,058
it-en	31,638	9,095	8,937	11,285	1,400	1,686	-	929	999
it-es	-	-	-	6,614	877	885	-	929	999
pt-en	9,158	3,590	4,254	4,918	1,747	2,286	29,940	1,002	1,019
pt-es	-	-	-	3,132	1,218	1,256	-	1,001	1,018
ru-en	12,112	9,497	8,634	-	-	-	4,829	970	1,124

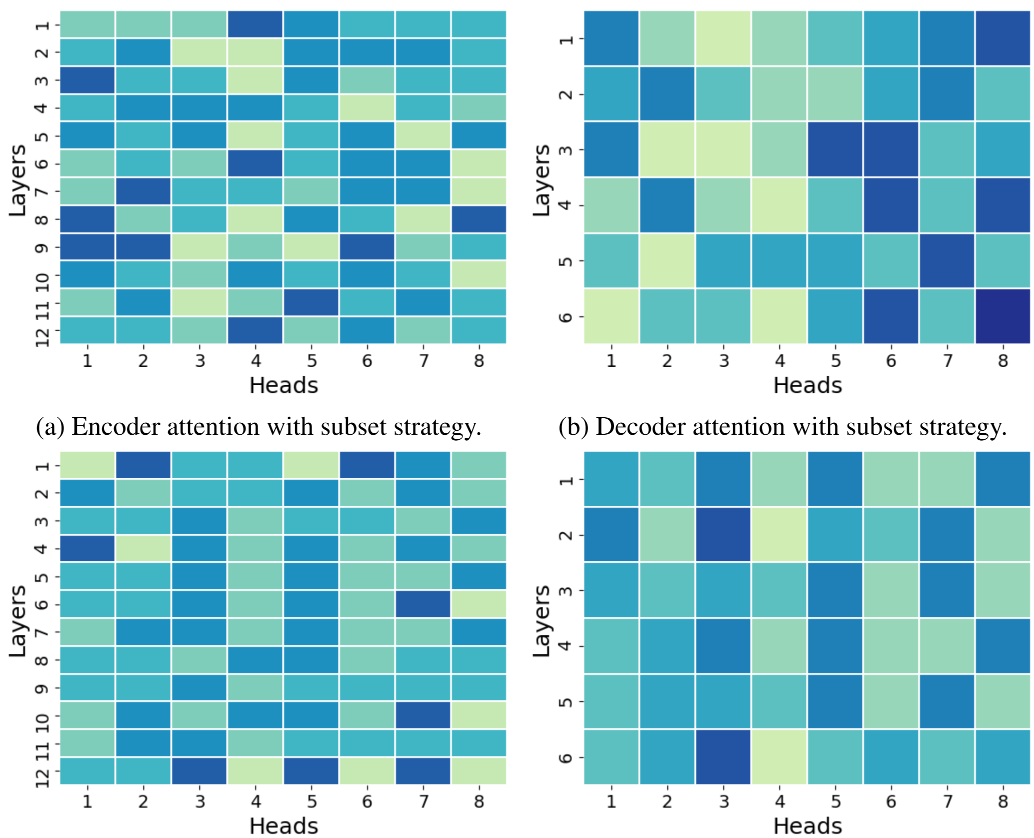
Data license. The machine translation data released for WMT shared tasks can be freely used for research purposes. The multilingual TEDx corpus is released under a CC BY-NC-ND 4.0 license, and can be freely downloaded. CoVoST 2 data is released under CC0 license. As for EuroParl, it is released under a Creative Commons license, and it is freely accessible and downloadable.

A.2 Experiment

The experiments were performed in the internal cluster. For machine translation experiments, we used 32 GPUs and each model was trained for around 3 days. On the task of speech recognition, models are trained on 8 GPUs. It took approximately 1 day for models to converge in multilingual setting, and 2 days in multi-domain setting. On the task of speech translation, the training time was also 1 day for multilingual models, and 2 days for multi-domain models. Speech translation models were trained with 8 GPUs.

A.3 Discussion

In this section, we provide insights into learned attention head selection with further result analysis.



(a) Encoder attention with subset strategy.

(b) Decoder attention with subset strategy.

(c) Encoder attention with group strategy.

(d) Decoder attention with group strategy.

Figure 4: Heatmap to visualize the load of attention heads (The darker a head is, the more languages it supports).

Load of Attention Heads. To gain an insight into the load of attention heads, we analyze how many languages an attention head is used by. With both subset and group strategies, we look into attention heads in encoder and decoder respectively. We study ASR models which learn language based attention selection on mTEDx data covering 8 languages. The language load of each attention head is measured by the number of languages sharing the given head. Fig. 4 visualizes the load of attention heads in each layer with a heatmap. The darkness reflects the load of an attention head.

By comparing encoder heads in Fig. 4(a) and (c), we note that group strategy results in more balanced load among attention heads than subset strategy, as there is less color variation in the heatmap of group strategy. Similar pattern could be observed in decoder, and decoder attention heads have more balanced load with group strategy.

Now we compare the load of attention heads across layers. With subset strategy, the load imbalance is observed in heads of almost every encoder and decoder layer from the color contrast in the heatmap. As for group strategy, the load is more balanced in heads of middle layers (i.e., encoder layers $5-9$ and decoder layers $3-5$) than those in bottom and top layers.

Head Selection in Encoder and Decoder. In our experiments, attention selection is applied to both encoder and decoder in ASR and ST experiments, considering that both encoder and decoder handle multiple languages. We want to measure how the model performance is affected by attention selection in encoder and decoder respectively. Taking the multilingual ASR as an example, Table 9 reports WER of models which enable attention selection in encoder only, in decoder only as well as in both encoder and decoder. We set the same hyperparameters as used in the experiment of multilingual ASR. When the attention selection is applied to encoder (or decoder) only, 4 attention heads are shared by all languages in each decoder (or encoder) layer.

Table 9: Ablation Study in WER (↓) of Multilingual Speech Recognition on mTEDx

Component with attention selection	Encoder only	Decoder only	Encoder+Decoder
Group strategy	42.2	46.2	40.0
Subset strategy	45.4	47.5	44.7

As is shown in Table 9, attention selection in only encoder (c.f. column "Encoder only") or decoder (c.f. column "Decoder only") would increase WER in comparison with the model with attention selection in both encoder and decoder (c.f. column "Encoder+Decoder"). We also note that attention head selection in encoder achieves lower WER than selection in decoder.