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FastAdaSP: Multitask-Adapted Efficient Inference for Large Speech Language Model

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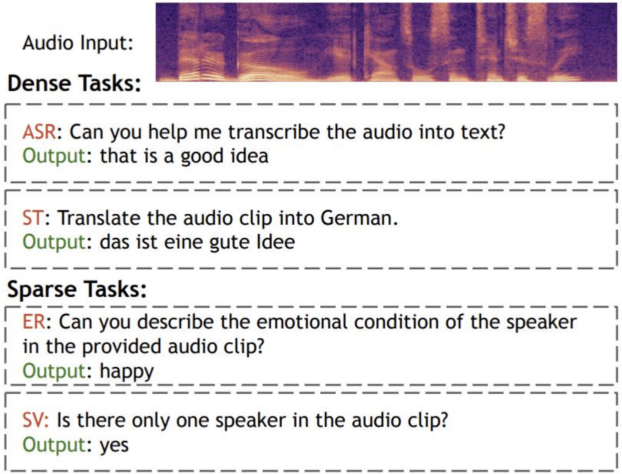
FastAdaSP - Motivation

Watanabe's
Audio and Voice Lab



- Speech Foundation Model/SpeechLM become larger and larger.
- Previous methods for optimizing large language model (LLM) inference, cannot universally applicable across all speech/audio-related tasks.

- We want to build…
  - A fast inference method design for audio/speech modality in MLLMs
  - Adaptively speed up all audio/speech related tasks
  - Could apply to all Speech LMs

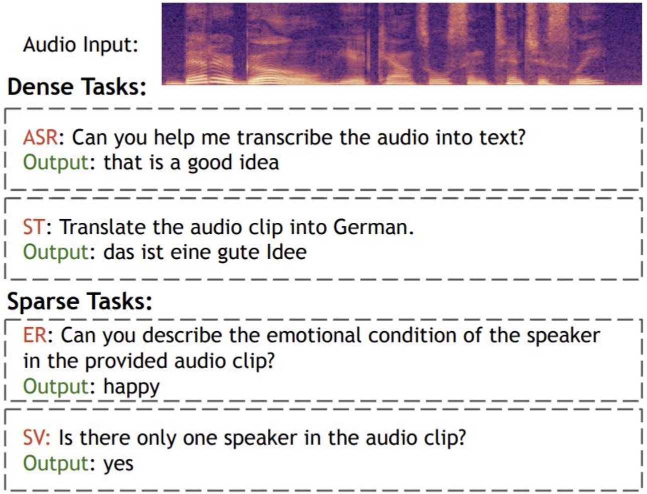
FastAdaSP - Related Works

Previous efficient inference works for LLM/MLLM

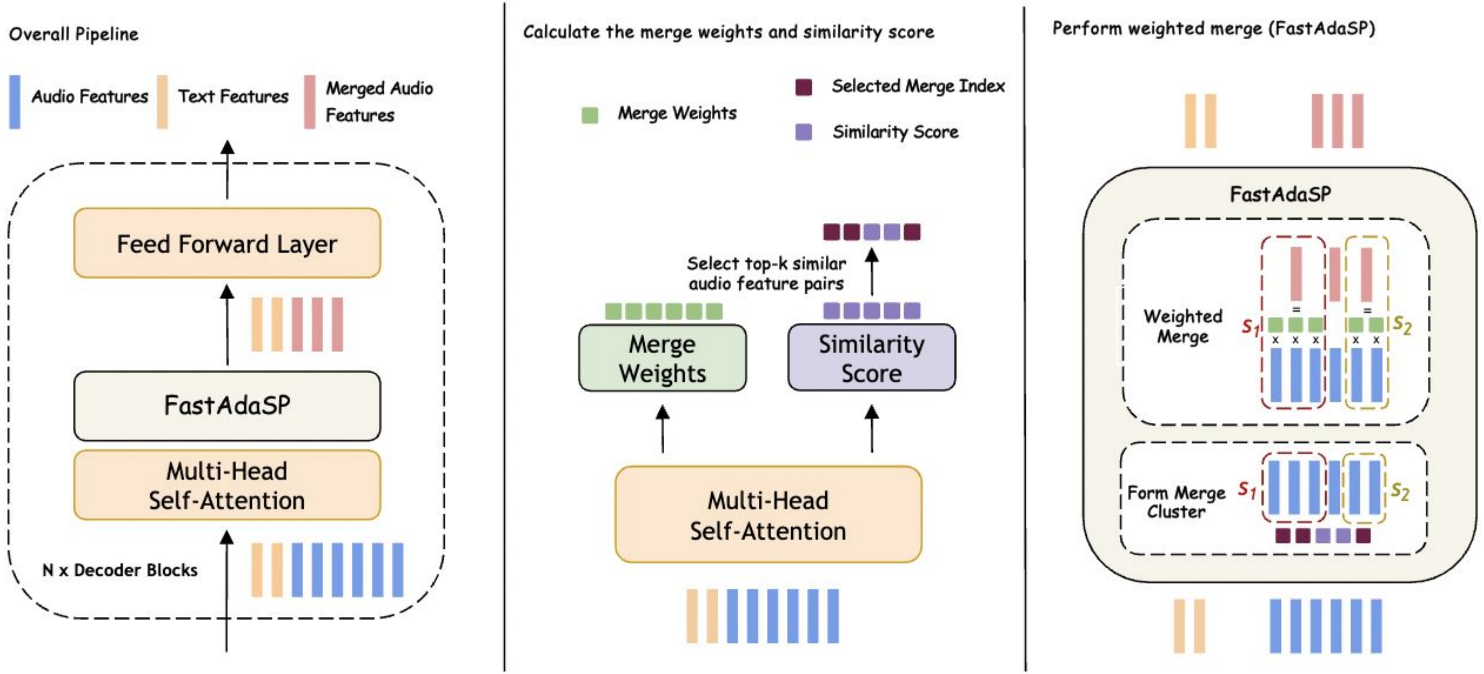
- Text:
  - H2O (Zhang, et al; 2023)
  - StreamingLLM (Xiao, et al; 2024)
  - etc.
- Visual:
  - FastV (Chen, et al; 2024)

FastAdaSP - Motivation

- However in Audio/Speech LM..



FastAdaSP - Method



Dense Strategy - Scheduler

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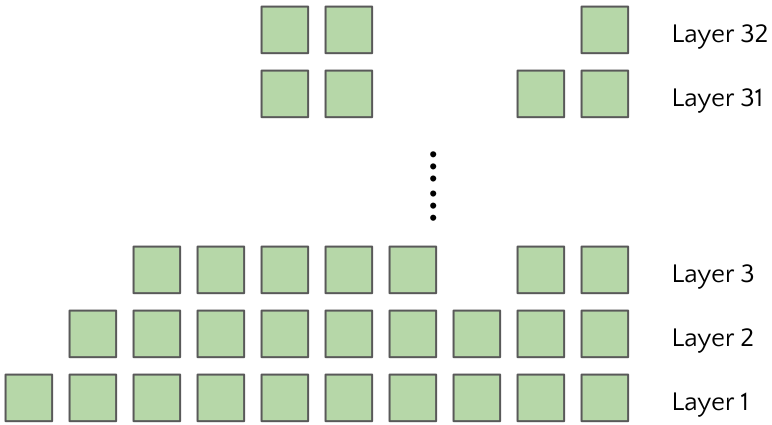


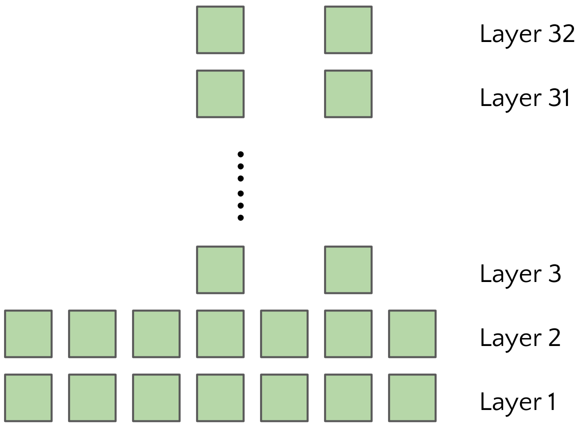
We designed an operation scheduler that smoothly merges tokens layer by layer to prevent aggressive token dropping in SpeechLM.

Dense Strategy - Scheduler

	ASR (WER% ↓)					ST (BLEU ↑)				
Full Token Baseline	2.25					21.56				
FLOPs Reduce	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%
Weighted Merge	**2.25**	**2.44**	3.25	10.51	93.14	20.94	20.03	18.41	14.45	8.74
Weighted Merge + Constant Schedule	2.27	2.49	**2.48**	**2.96**	**4.73**	**21.47**	**20.72**	**19.81**	**18.54**	**17.45**
Weighted Merge + Decay Schedule	2.27	2.57	2.74	3.53	6.09	20.92	20.59	19.66	18.06	16.40

Table 8: The effectiveness of scheduler on WavLLM Dense tasks (ASR and ST)

Sparse Strategy - Layer Selection



We use Transfer Entropy to guide layer selection for token reduction;

TE defined as:

$$\left| H\left(\Phi\left(F_{\text{final}}; \mathbb{W}_{\text{final}}\right)\right) - H\left(F_{\text{final}} \mid \Phi\left(F_i; \mathbb{W}_i\right)\right) \right|$$

Which:

$\Phi(\cdot;\cdot)$ is the token reduction operation

F is the embedding output

H() is the entropy calculation

Sparse Strategy - Layer Selection

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FLOPs Reduce	TE	TE Rank	10%	20%	30%	40%	50%
Layer 2	2.20	4	54.78	54.30	54.06	52.91	52.10
Layer 9	2.17	3	**55.51**	54.30	53.61	53.30	51.50
Layer 12	2.29	5	54.75	53.96	53.44	52.72	48.35
Layer 15	2.11	2	53.98	54.06	53.02	50.57	-
Layer 3 (Selected)	2.06	1	55.17	**55.05**	**54.40**	**53.86**	**52.14**

Table 6: **Layer Selection Experiments:** Comparison on the performance between different layers on Qwen-Audio ER task (Full token baseline accuracy: 54.80%)

FastAdaSP - Exps(QwenAudio)

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	ASR (WER% ↓)					ST (BLEU ↑)				
Full Token Baseline	2.21					41.46				
FLOPs Reduce	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%
Random Merge	2.43	3.39	8.21	27.53	169.96	40.63	39.35	37.01	32.39	24.3
Random Evict	5.70	21.42	61.04	184.59	342.88	38.39	28.22	14.98	6.29	-
A-ToMe (Li et al., 2023)	2.20	3.26	13.91	71.56	273.49	41.24	39.87	36.52	25.35	8.64
FastV (Chen et al., 2024)	12.54	54.40	110.42	179.58	258.78	41.12	40.31	38.45	34.74	27.14
FastAdaSP-Dense **Decay Schedule**	**2.19**	2.23	2.51	4.37	**15.24**	41.41	41.05	40.51	39.02	35.79
FastAdaSP-Dense **Constant Schedule**	2.22	**2.21**	**2.30**	**3.57**	16.01	**41.47**	**41.30**	**40.83**	**39.81**	**37.04**

Table 9: Comparison between FastAdaSP with other token reduction methods on Qwen-Audio **dense tasks**

	ER (ACC% ↑)					AC (CIDEr ↑ | SPICE ↑ | SPIDEr ↑)				
Full Token Baseline	54.80					0.45 | 0.13 | 0.29				
FLOPs Reduce	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%
Random Merge	51.80	48.00	43.80	39.20	32.30	0.44 | 0.13 | 0.29	0.43 | 0.13 | 0.28	0.41 | 0.13 | 0.27	0.41 | 0.12 | 0.26	0.38 | 0.12 | 0.25
Random Evict	52.80	48.20	42.00	34.61	23.14	0.43 | 0.13 | 0.28	0.42 | 0.13 | 0.27	0.38 | 0.12 | 0.25	0.31 | 0.10 | 0.20	0.12 | 0.07 | 0.14
A-ToMe (Li et al., 2023)	54.91	54.70	54.20	**53.90**	51.60	0.44 | 0.13 | 0.29	0.44 | 0.13 | 0.29	0.43 | 0.13 | 0.28	0.41 | 0.13 | 0.27	0.39 | 0.12 | 0.28
FastV (Chen et al., 2024)	54.80	53.80	53.50	52.10	50.38	0.44 | 0.13 | 0.29	**0.45 | 0.13 | 0.29**	0.45 | 0.13 | 0.29	0.44 | 0.13 | 0.28	0.43 | 0.13 | 0.28
FastAdaSP-Sparse	**55.17**	**55.05**	**54.40**	53.86	**52.14**	**0.45 | 0.13 | 0.29**	0.44 | 0.13 | 0.29	**0.45 | 0.13 | 0.29**	**0.44 | 0.13 | 0.28**	**0.43 | 0.13 | 0.28**

Table 10: Comparison between FastAdaSP with other token reduction methods on Qwen-Audio **sparse task**

FastAdaSP - Exps(Efficiency)

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Beam Size	Audio Length (s)	Token Reduce %	FLOPs Reduction % ↑	Real Time Factor ↓	Pre-filling Latency (s) ↓	Decoding Latency (s) ↓	Throughput (token/s) ↑
1	120	Full Token	0.00	0.054	0.79	5.75	12.86
		50	48.62	0.044	0.77	4.57	13.57 (1.05x)
5	120	Full Token	0.00	0.137	3.11	13.32	5.48
		50	48.40	0.092	3.09	8.01	8.87 (1.61x)
1	240	Full Token	0.00	0.044	1.70	8.90	8.09
		50	49.21	0.036	1.59	7.02	9.69 (1.20x)
5	240	Full Token	0.00	0.126	6.72	23.55	3.10
		50	49.21	0.077	6.48	11.89	5.72 (**1.84x**)

Table 12: **Long Sequence Computational cost experiments on A100.** Long sequence audio samples (120s and 240s) input on WavLLM using one A100 80GB GPU

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Links:

- https://fastadasp.github.io/
- https://github.com/yichen14/FastAdaSP

References:

- Liang Chen, Haozhe Zhao, Tianyu Liu, Shuai Bai, Junyang Lin, Chang Zhou, & Baobao Chang. (2024). An Image is Worth 1/2 Tokens After Layer 2: Plug-and-Play Inference Acceleration for Large Vision-Language Models.
- Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, & Mike Lewis. (2024). Efficient Streaming Language Models with Attention Sinks.
- Zhenyu Zhang, Ying Sheng, Tianyi Zhou, Tianlong Chen, Lianmin Zheng, Ruisi Cai, Zhao Song, Yuandong Tian, Christopher Ré, Clark Barrett, Zhangyang Wang, & Beidi Chen. (2023). H$_2$O: Heavy-Hitter Oracle for Efficient Generative Inference of Large Language Models.