

Training Audio Captioning Models without Audio

^{1,2}Soham Deshmukh, ¹Benjamin Elizalde, ¹Dimitra Emmanouilidou,

²Bhiksha Raj, ²Rita Singh, ¹Huaming Wang

¹Microsoft, ²Carnegie Mellon University

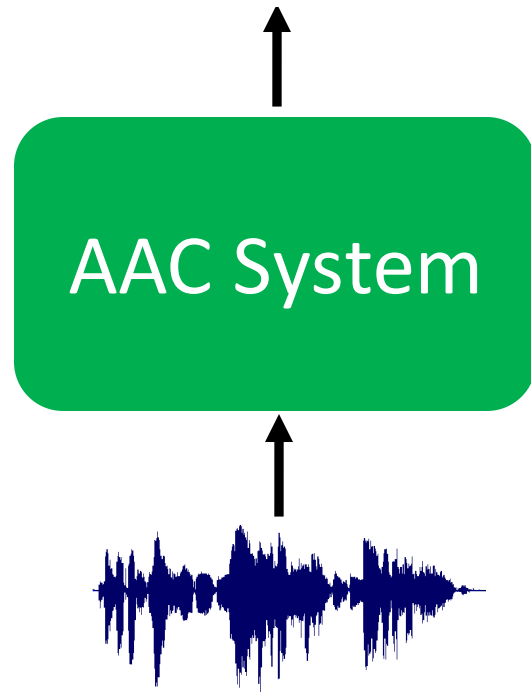


Overview

Leverage the multimodal space from a Contrastive Language Audio Pretraining (CLAP) to train an Audio Captioning system with **only text**.

Automated Audio Captioning (AAC) generates a description given an audio stream.

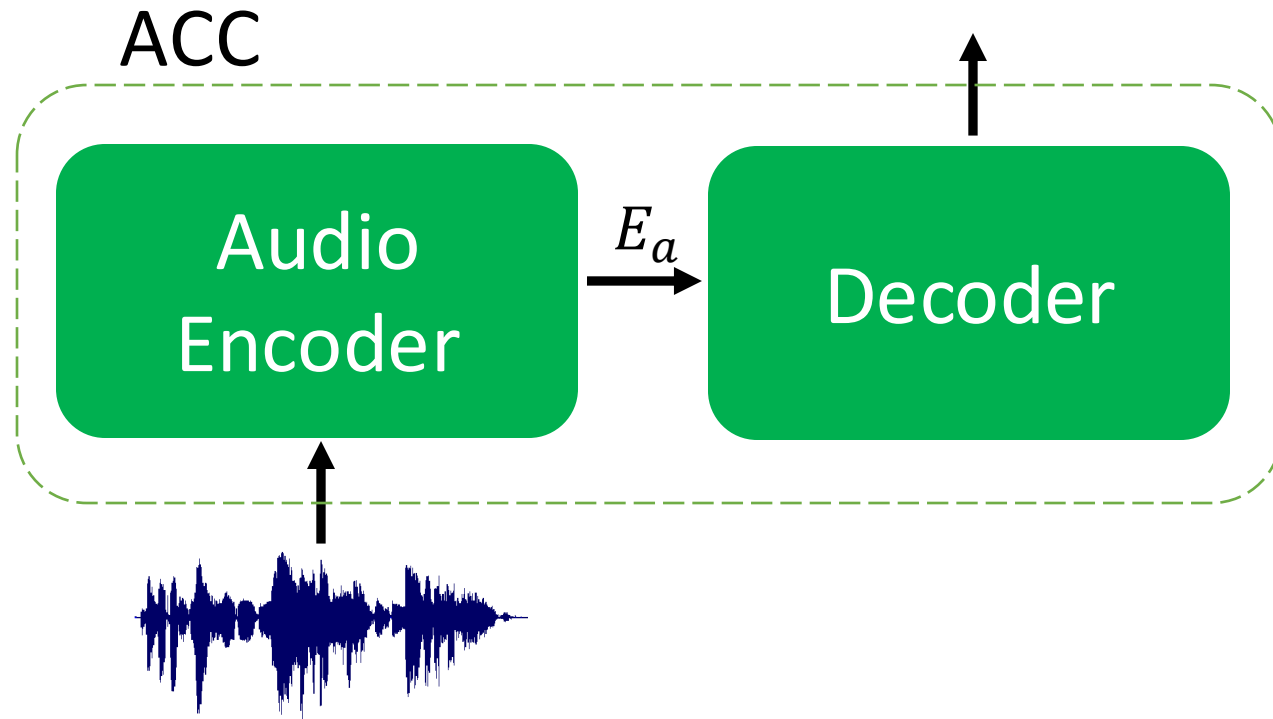
Children playing with birds chirping in
the background



**Different from
Speech Transcriptions and
Closed Captioning**

Baseline architecture for AAC

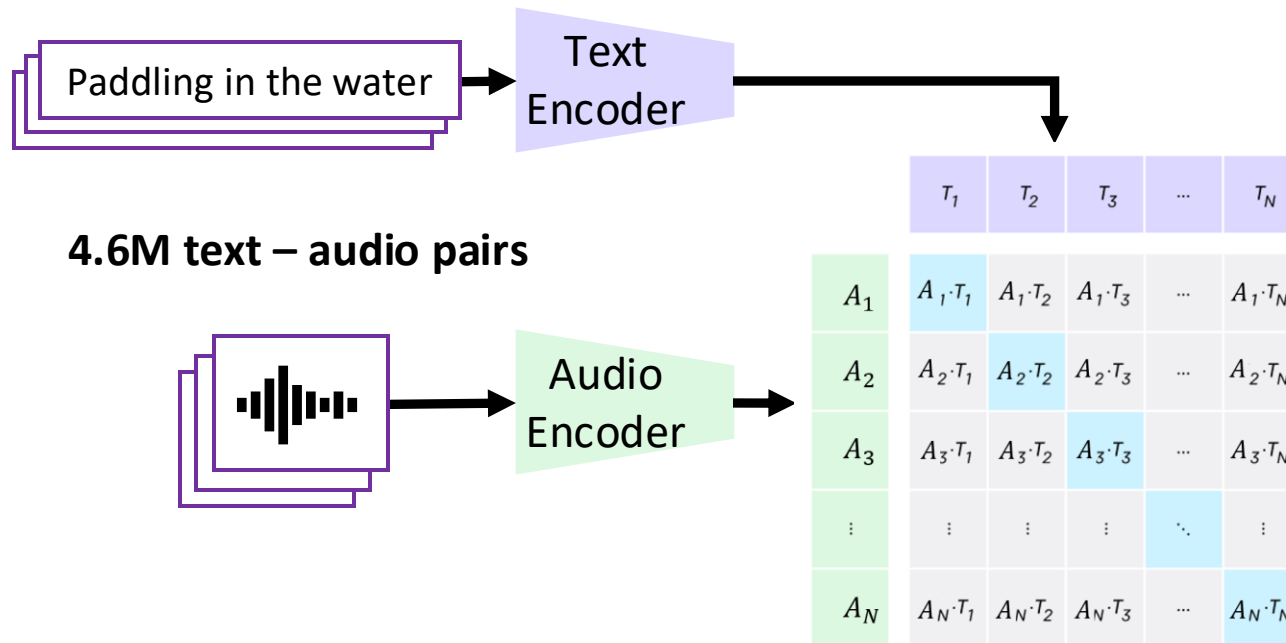
Children playing with birds chirping in
the background



Training and Inference
need
an audio encoder

Contrastive Language-Audio Pretraining (CLAP)

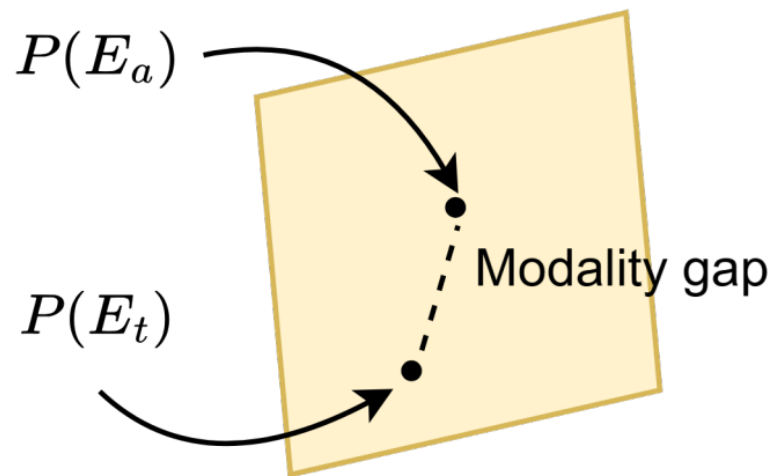
Pretraining stage



Minimize
average cross-entropy
between audio and text

Multimodal space of CLAP

Audio-text joint
multimodal space



An AAC model learns $P(\text{Caption}|E_a)$

In CLAP, $P(\text{Caption}|E_a) = P(\text{Caption}|E_t)$

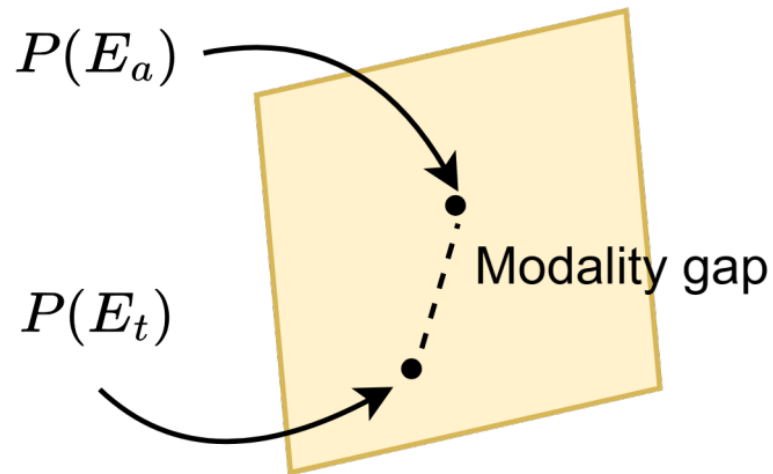
Therefore, for AAC, we can instead learn $P(\text{Caption}|E_t)$

Implications:

1. Use CLAP's text encoder for training and the audio encoder for inference.
2. Enable text-only training, no need for aligned audio and caption.

However, there exists a modality gap

Audio-text joint
multimodal space



In practice,

$$P(\text{Caption}|E_t) \neq P(\text{Caption}|E_a)$$

instead,

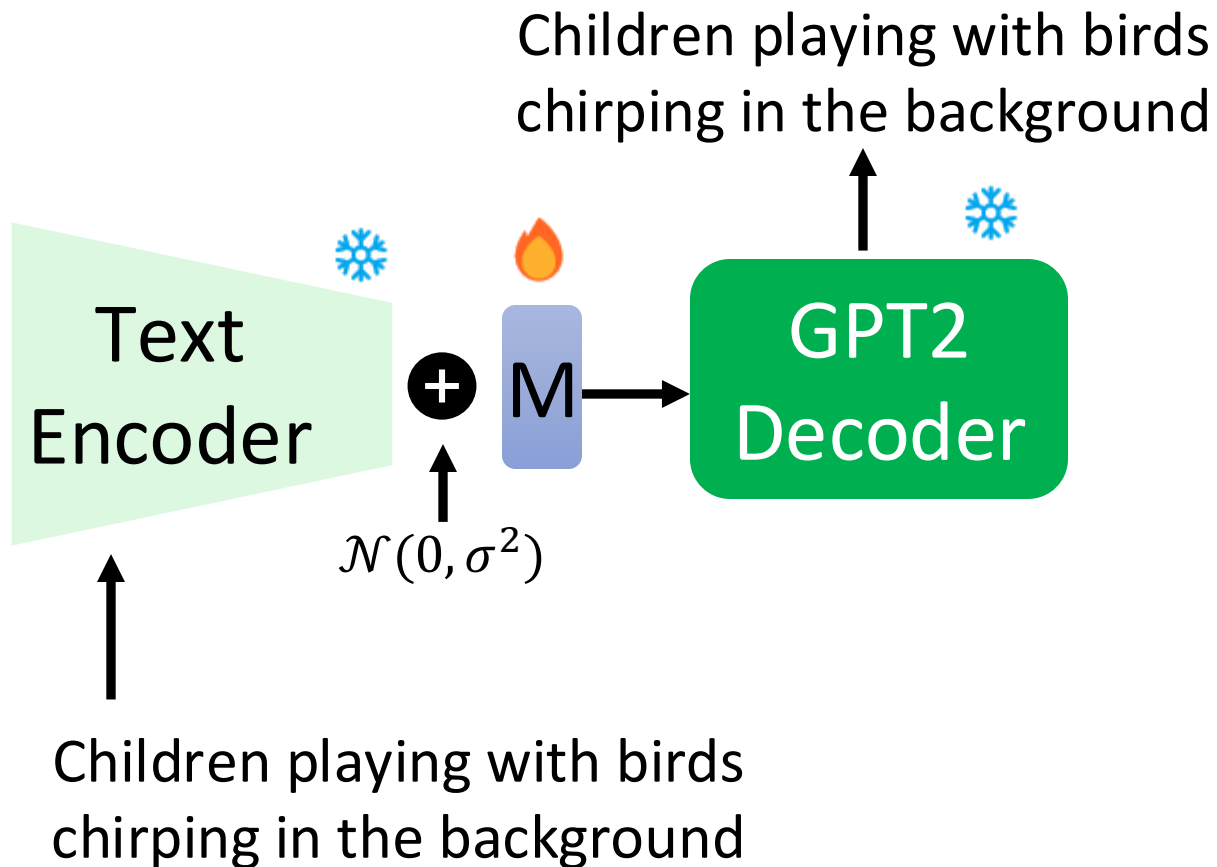
$$P(\text{Caption}|E_t) \sim P(\text{Caption}|E_a)$$

The gap **limits** the direct swap of audio and text encoders.

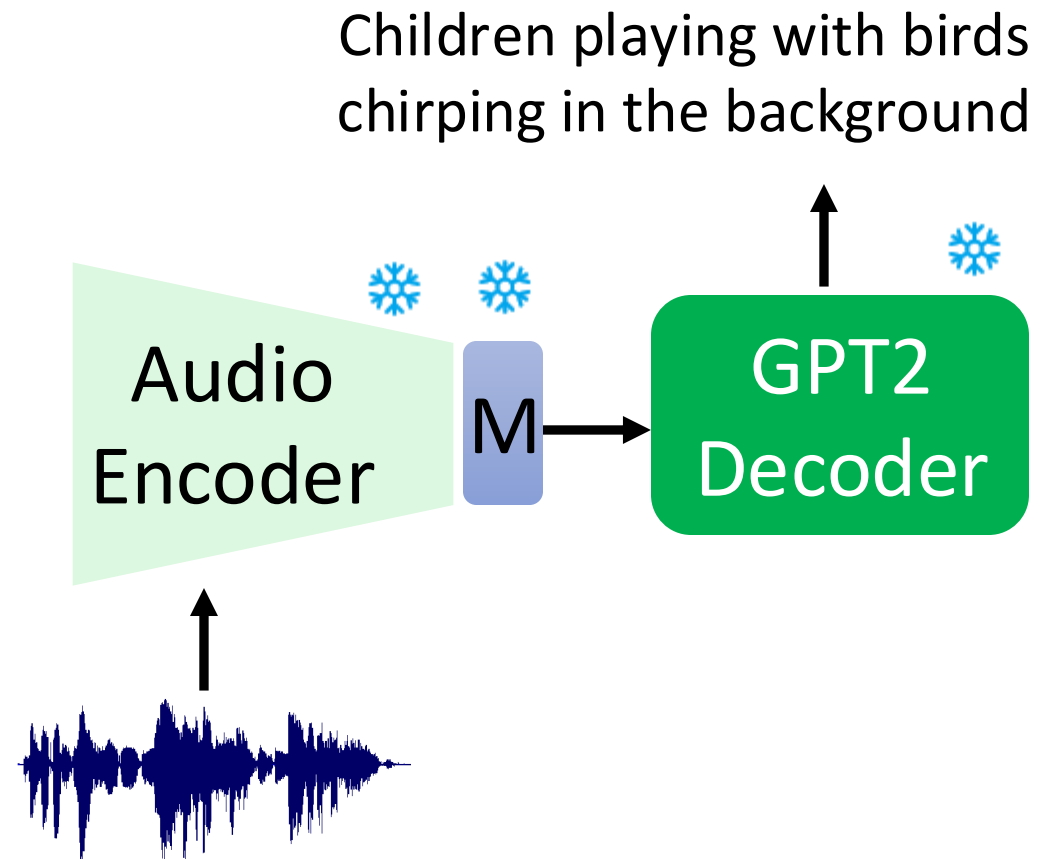
To **bridge the gap**, we added zero-mean Gaussian noise at training

Proposed Text-only training for AAC

Training stage



Inference



AAC with CLAP's audio encoder for audio-text training

Model	Eval. dataset	BLUE ₁	BLUE ₂	BLUE ₃	BLUE ₄	METEOR	ROUGE _L	CIDEr	SPICE	SPIDER
Chen et al.	AudioCaps	0.489	0.292	0.178	0.106	0.152	0.346	0.265	0.093	0.179
Gontier et al.	AudioCaps	0.635	0.461	0.322	0.219	0.208	0.450	0.612	0.153	0.383
Mei et al.	AudioCaps	0.682	0.507	0.369	0.266	0.238	0.488	0.701	0.166	0.434
Kim et al.	AudioCaps	0.708	0.547	0.402	0.283	0.238	0.499	0.710	0.167	0.438
Audio-text (proposed)	AudioCaps	0.647	0.480	0.337	0.223	0.223	0.462	0.729	0.181	0.455
Chen et al.	Clotho	0.516	0.325	0.215	0.141	0.153	0.350	0.314	0.102	0.208
Gontier et al.	Clotho	0.461	0.282	0.182	0.117	0.136	0.318	0.251	0.083	0.167
Mei et al.	Clotho	0.516	0.318	0.204	0.127	0.157	0.351	0.313	0.105	0.209
Kim et al.	Clotho	0.539	0.346	0.227	0.142	0.159	0.366	0.319	0.111	0.215
Audio-text (proposed)	Clotho	0.574	0.375	0.250	0.155	0.173	0.381	0.398	0.123	0.261

We achieved SoTA performance in both datasets

AAC with CLAP's text encoder for text-only training

Model	Eval. dataset	BLUE ₁	BLUE ₂	BLUE ₃	BLUE ₄	METEOR	ROUGE _L	CIDEr	SPICE	SPIDER
Chen et al.	AudioCaps	0.489	0.292	0.178	0.106	0.152	0.346	0.265	0.093	0.179
Gontier et al.	AudioCaps	0.635	0.461	0.322	0.219	0.208	0.450	0.612	0.153	0.383
Mei et al.	AudioCaps	0.682	0.507	0.369	0.266	0.238	0.488	0.701	0.166	0.434
Kim et al.	AudioCaps	0.708	0.547	0.402	0.283	0.238	0.499	0.710	0.167	0.438
Text-only (proposed)	AudioCaps	0.645	0.481	0.338	0.227	0.220	0.458	0.697	0.178	0.437
Audio-text (proposed)	AudioCaps	0.647	0.480	0.337	0.223	0.223	0.462	0.729	0.181	0.455
Chen et al.	Clotho	0.516	0.325	0.215	0.141	0.153	0.350	0.314	0.102	0.208
Gontier et al.	Clotho	0.461	0.282	0.182	0.117	0.136	0.318	0.251	0.083	0.167
Mei et al.	Clotho	0.516	0.318	0.204	0.127	0.157	0.351	0.313	0.105	0.209
Kim et al.	Clotho	0.539	0.346	0.227	0.142	0.159	0.366	0.319	0.111	0.215
Text-only (proposed)	Clotho	0.524	0.339	0.222	0.136	0.173	0.371	0.379	0.132	0.256
Audio-text (proposed)	Clotho	0.574	0.375	0.250	0.155	0.173	0.381	0.398	0.123	0.261

Achieves comparable performance to traditional audio-text training

Training with additional ~400k LLM generated captions (WavCaps)

Model	Eval. dataset	BLUE ₁	BLUE ₂	BLUE ₃	BLUE ₄	METEOR	ROUGE _L	CIDEr	SPICE	SPIDEr
Text-only	AudioCaps	0.645	0.481	0.338	0.227	0.220	0.458	0.696	0.178	0.437
Text-only [†]	AudioCaps	0.653	0.484	0.342	0.232	0.226	0.459	0.697	0.179	0.438
Text-only	Clotho	0.524	0.339	0.222	0.136	0.173	0.371	0.379	0.132	0.256
Text-only [†]	Clotho	0.530	0.342	0.224	0.143	0.164	0.367	0.377	0.117	0.247

Performance improved overall, especially on n-gram matching metrics



Infusing style with stylized captions

Train Dataset	Eval. dataset	BLUE ₁	BLUE ₂	SPIDE _r
Original Clotho	Humor Clotho	0.370	0.162	0.092
Humor Clotho	Humor Clotho	0.410	0.214	0.102

Original: “Sand is being shoveled and dumped on the ground”,

Humorous: “Sand relocation program: from shovel to ground, it’s a gritty story”.

Text-only training enables faster adaptation to different styles

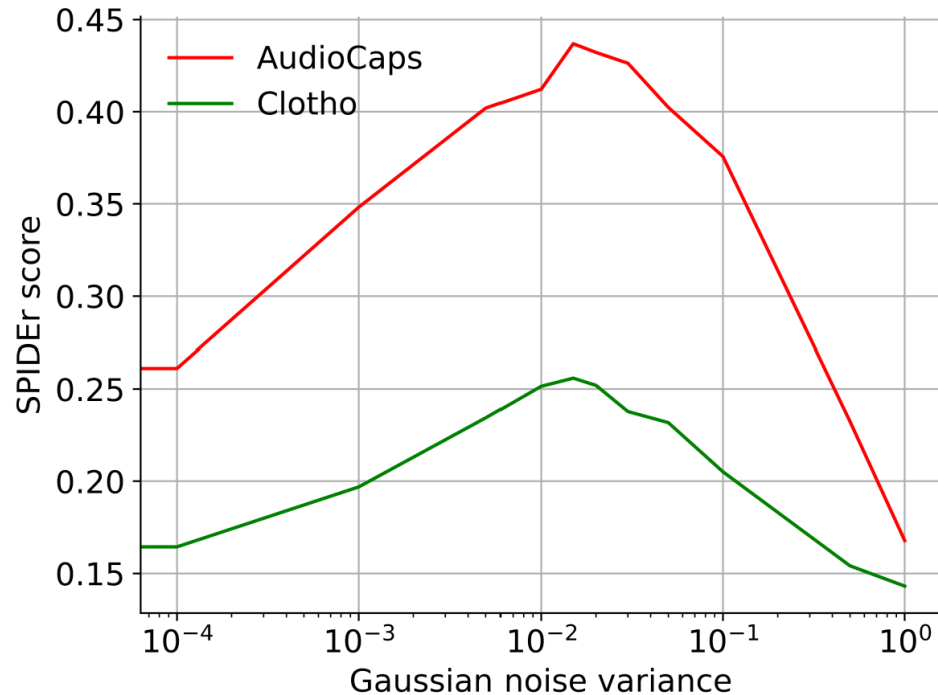
Takeaways

1. We introduced a text-only training approach for AAC.
2. We leveraged from the multimodal space learned by contrastive models.
3. Our text-only training achieves competitive results with the SoTA, while enabling improvement and stylization of captions.

Soham Deshmukh, Benjamin Elizalde
{sdeshmukh, benjaminm}@microsoft.com

Appendix

Effect of variance of Gaussian Noise



The variance of Gaussian noise can be approximated by:

infinity norm between the audio and text embeddings of randomly chosen examples

There exists a better value of noise variance irrespective of target dataset

Gaussian noise vs trained linear adapter

Model	Adapter	Eval. dataset	BLUE ₁	BLUE ₂	BLUE ₃	BLUE ₄	METEOR	ROUGE _L	CIDEr	SPICE	SPIDEr
Text-only	Gaussian	AudioCaps	0.645	0.481	0.338	0.227	0.220	0.458	0.696	0.178	0.437
Text-only	Linear ₁	AudioCaps	0.609	0.423	0.286	0.181	0.204	0.429	0.602	0.174	0.388
Text-only	Gaussian	Clotho	0.524	0.339	0.222	0.136	0.173	0.371	0.379	0.132	0.256
Text-only	Linear ₁	Clotho	0.568	0.375	0.251	0.158	0.172	0.378	0.394	0.127	0.261

Table 3: All models use AudioCaps and Clotho datasets in training. Symbol [†] indicates that LLM-generated text [18] is added in training.