Paper ID: 57

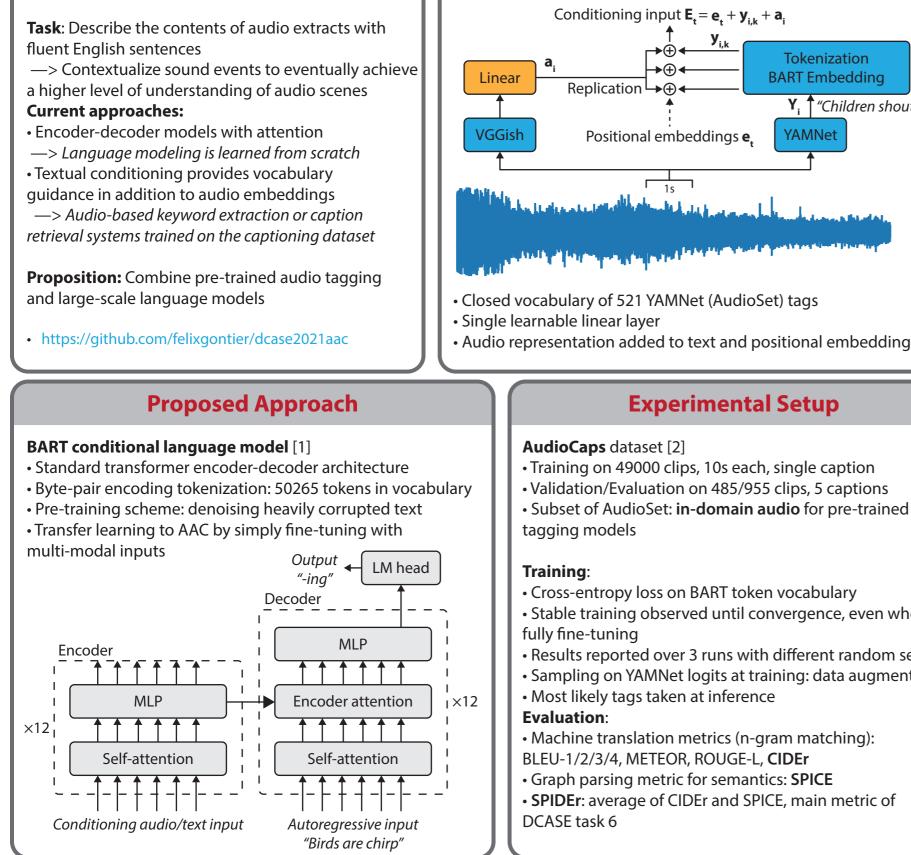
## Automated Audio Captioning by Fine-tuning BART on AudioSet Tags

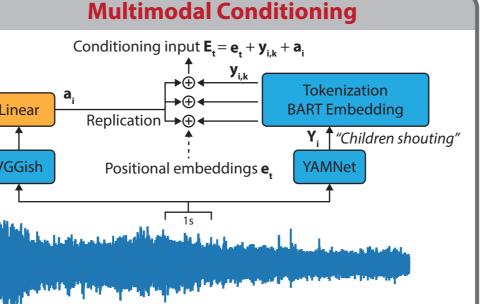


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#### Context





- Closed vocabulary of 521 YAMNet (AudioSet) tags
- Audio representation added to text and positional embeddings

#### **Experimental Setup**

- Training on 49000 clips, 10s each, single caption
- Validation/Evaluation on 485/955 clips, 5 captions
- Cross-entropy loss on BART token vocabulary
- Stable training observed until convergence, even when
- Results reported over 3 runs with different random seeds
- Sampling on YAMNet logits at training: data augmentation
- Most likely tags taken at inference
- Machine translation metrics (n-gram matching):
- SPIDEr: average of CIDEr and SPICE, main metric of

#### **Conditioning setup** Sequential embeddings are critical to captioning Text-only conditioning

- is better than audio-only

#### Model performance

- On par or better than the state of the art on AudioCaps

```
M
  TopDown-A
     Koizumi
      Eren e
BART + YAN
          Hu
```

#### **Complementary experiments**

- Random initialization: The performance improvement from BART pre-training is limited with sufficient amounts of training data
- Freezing: BART decoder is already effective to model caption structure Output
- Capacity: A marginal decrease in performance is observed with 3 times fewer parameters
- —> Low diversity in caption structure and vocabulary?
- Task-specific fine-tuning: The initial training loss is
- lower with summarization checkpoints

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#### **References:**

[1] Lewis et al., BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. ACL 2020. [2] Kim et al., AudioCaps: Generating captions for audio in the wild. NAACL 2019

[3] Koizumi et al., Audio captioning using pre-trained large-scale language model guided by audio-based similar caption retrieval. 2020 [4] Eren et al., Audio captioning based on combined audio and semantic embeddings. ISM 2020

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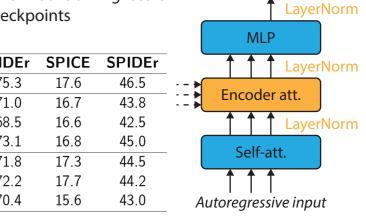
#### Results

VGGish	PANNs	YAMNet	CIDEr	SPICE	SPIDEr
	×		6.5 (2.5)	6.1 (0.9)	6.3 (1.7)
×			37.6 (8.0)	11.9 (1.3)	24.7 (4.6)
		×	54.7 (0.6)	14.1 (0.2)	34.4 (0.4)
×		×	63.9 (1.0)	15.9 (0.3)	39.9 (0.7)
	×	×	75.3 (0.9)	17.6 (0.3)	46.5 (0.6)

—> Better use of the text-only BART pre-training setting? Both PANNs and VGGish complement YAMNet, PANNs are more informative

# • Higher BLEU-1/2/3 than reference captions cross-validation (human score)

1odel	CIDEr	SPICE	SPIDEr
AlignedAtt [2]	59.3	14.4	36.9
ni et al. [3]	50.3	13.9	32.1
et al. [4]	75.0	-	-
MNet + PANNs	75.3	17.6	46.5
uman	91.3	21.6	56.5



LM head