

# On the Contributions of Visual and Textual Supervision in Low-Resource Semantic Speech Retrieval

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### **Overview**

- <u>Background</u>: Visual grounding is a commonly used source of weak supervision for tasks involving untranscribed spoken data (e.g. [1,2]).
- <u>Open question</u>: Does visual grounding still help if we have text annotations during training?
- <u>Our setting</u>: A low-resource setting where a fraction of the spoken training corpus is transcribed.
- <u>Our work:</u> Explores how to best combine the two modalities for *semantic speech retrieval*

Query word	Retrieved utterance
kids	a group of young boys playing soccer
beach	a dog retrieves a branch from a beach

# Multi-Task Learning (MTL) Approach

What are the multiple tasks?

#### Visually supervised task (MTL-visSup)

Trained on *image-speech pairs*<sup>1</sup>. An external *image tagger*<sup>2</sup> provides weak labels as ground truth.

#### Textually supervised task (MTL-textSup)

Trained on *speech-text pairs*<sup>3</sup>. Each transcript provides a multi-hot bag-of-words vector as ground truth.

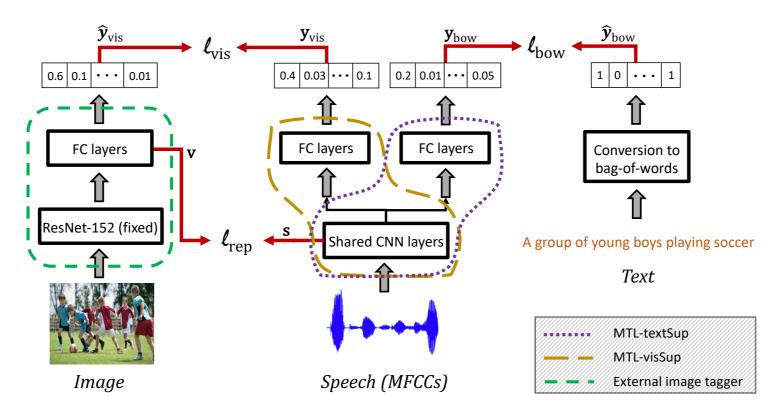
#### Unsupervised representation learning

Trained using the intermediate visual and speech representations. The former is fixed; the latter is updated during training.

#### What are the loss functions?

Supervised task losses ( $sup \in \{vis, bow\}$ ): summed cross entropy between the predicted and ground truth vectors.

$$\begin{split} \ell_{\sup} &= -\sum_{w=1}^{|N_{\sup}|} \left\{ \hat{y}_{\sup,\mathsf{w}} \log y_{\sup,\mathsf{w}} + \right. \\ & \left. \left. \left(1 - \hat{y}_{\sup,\mathsf{w}}\right) \log[1 - y_{\sup,\mathsf{w}}] \right\} \end{split} \end{split}$$



Representation loss: margin-based contrastive loss with margin m, positive pair  $\{v, s\}$ , negative pairs  $\{v', s\}$  and  $\{v, s'\}$ , and cosine distance.

$$\ell_{\text{rep}} = \left\{ \frac{1}{|V|} \sum_{\boldsymbol{v}' \in V} \max[0, m + d_{\cos}(\boldsymbol{v}, \boldsymbol{s}) - d_{\cos}(\boldsymbol{v}', \boldsymbol{s})] + \frac{1}{|S|} \sum_{\boldsymbol{s}' \in S} \max[0, m + d_{\cos}(\boldsymbol{v}, \boldsymbol{s}) - d_{\cos}(\boldsymbol{v}, \boldsymbol{s}')] \right\}$$

Total loss: weighted sum of the three losses.

$$\ell = \alpha \cdot \ell_{\text{vis}} + \beta \cdot \ell_{\text{bow}} + (1 - \alpha - \beta) \cdot \ell_{\text{rep}}$$

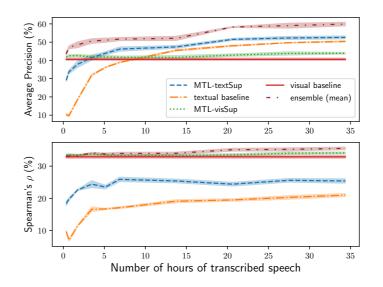
How is the inference done?

Input: Spoken utterances

*Output*: Scores from either MTL-visSup ( $y_{vis}$ ) or MTL-textSup ( $y_{bow}$ ) or a combination of the two

## Main Results

The models are evaluated on a corpus of *semantic relevance judgements*<sup>4</sup> (collected by Kamper et al. [1]).



<sup>1</sup>The Flickr8k Audio Captions Corpus consisting of  $\sim$ 8k images paired with 5 spoken captions each amounting to a total of  $\sim$ 46 hours of speech data ( $\sim$ 34 hours training,  $\sim$ 6 hours dev, and  $\sim$ 6 hours test). <sup>2</sup>ImageNet pre-trained fixed ResNet followed by fully connected layers trained on the union of MSCOCO and Flickr30k, with  $\sim$ 149k images ( $\sim$ 107k training,  $\sim$ 42k dev).

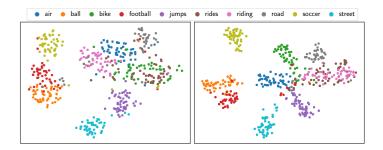
<sup>3</sup>Written transcripts of the Flickr8k Audio Captions. We use subsets of these transcripts with varying sizes: from just ~21 minutes to the complete ~34 hours of labelled speech.

<sup>4</sup>~1k utterances from the Flickr8k Audio Captions Corpus with their semantic relevance for each of 67 query words. Each (utterance, keyword) pair was labeled by 5 annotators. Majority vote of the annotators ("hard labels") and the actual number of votes ("soft labels") for evaluation.



## **Additional Observations**

- Adding representation loss gives a gain of 7-15% on average precision.
- Higher output dimensionality acts as a regularizer in lower supervision conditions.
- The proposed model outperforms pre-training and hierarchical MTL.
- t-SNE visualization of the learned representations in the text baseline (left) and MTL-textSup (right)



## Conclusion

- Visual grounding helps even in the presence of textual supervision.
- Proposed MTL approach significantly improves performance at all levels of supervision.
- Joint training with representation loss helps.

# **Future Work**

*Domain extension:* Does our visually grounded model perform well on speech not describing visual scenes?

*Modify text encoder:* Can we explicitly encode semantics in the textual supervision?

## References

- [1] D. Harwath *et al.* Unsupervised Learning of Spoken Language with Visual Context, *NIPS 2016*.
- [2] H. Kamper *et al.* Semantic Speech Retrieval with a Visually Grounded Model of Untranscribed Speech, *IEEE TASLP*, vol. 27, pp. 89-98, 2019.