Visually grounded learning of keyword prediction from untranscribed speech

Interspeech, August 2017

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Success in speech recognition

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TECHNOLOGY LAB —

Microsoft releases open source toolkit used to build human-level speech recognition

Microsoft wants to put machine learning everywhere.

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Speech Recognition Gets Conversational

By ROBERT MCMILLAN

May 28, 2015 12:54 pm ET

Success in speech recognition

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[Xiong et al., arXiv'16]; [Saon et al., arXiv'17]

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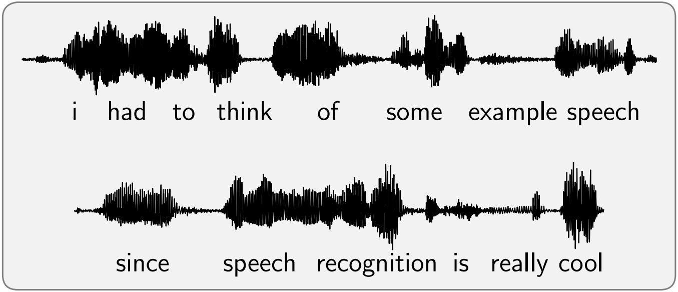
- Data: 2000 hours transcribed speech audio; ∼350M/560M words text

Success in speech recognition



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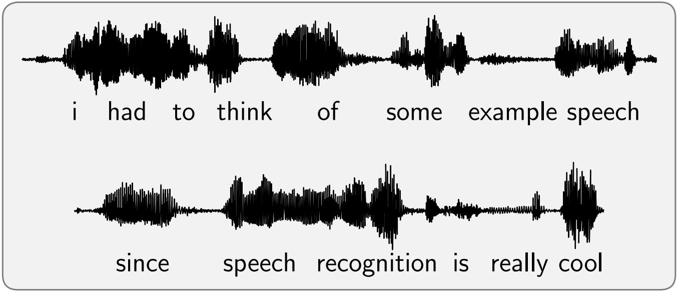

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- Google Voice: English, Spanish, German, ..., Zulu (∼50 languages)
- Data: 2000 hours transcribed speech audio; ∼350M/560M words text
- Can we do this for all 7000 languages spoken in the world?

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- Get insight into human **language acquisition** [Räsänen and Rasilo, '15]
- Language acquisition in **robots** [Roy, '99]; [Renkens and Van hamme, '15]
- Analysis of audio for unwritten languages [Besacier et al., '14]

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- New **insights** and models for speech processing [Jansen et al., '13]

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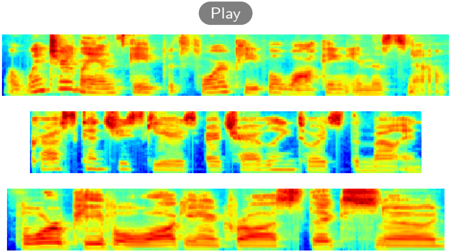
- We consider images paired with unlabelled spoken captions:



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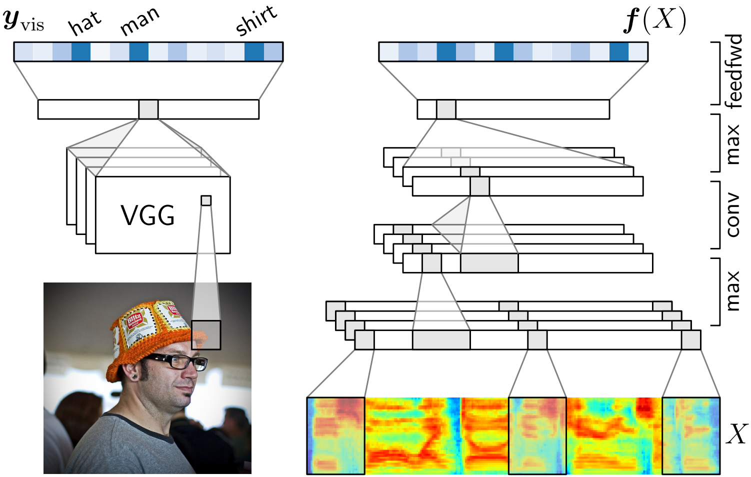

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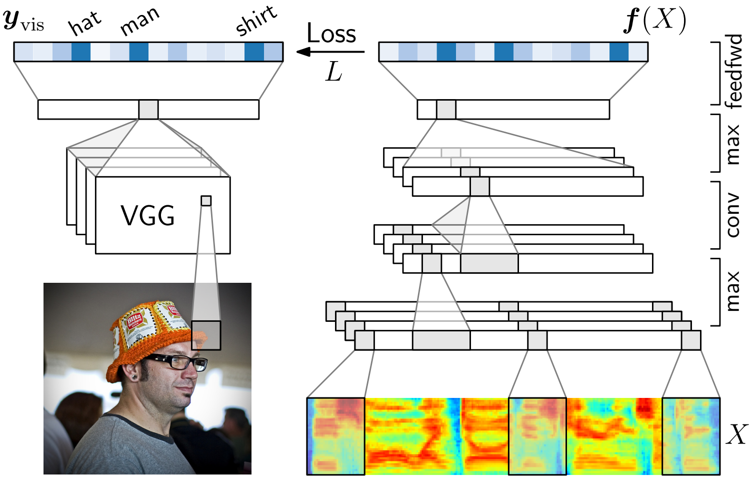

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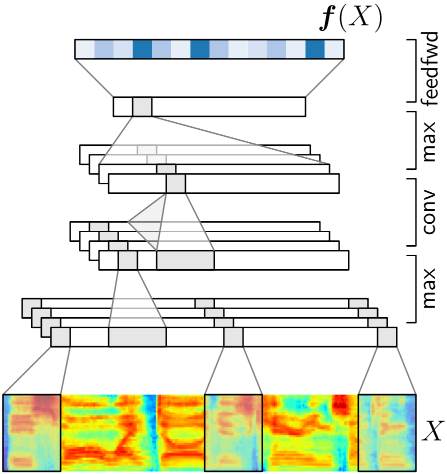

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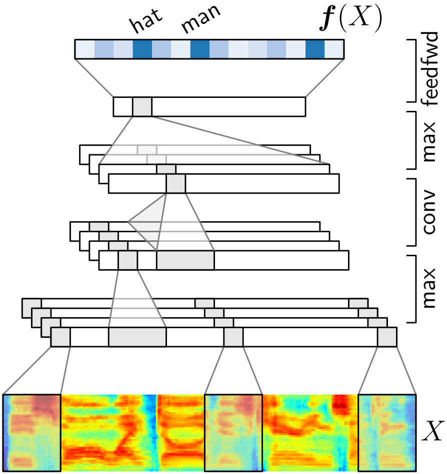
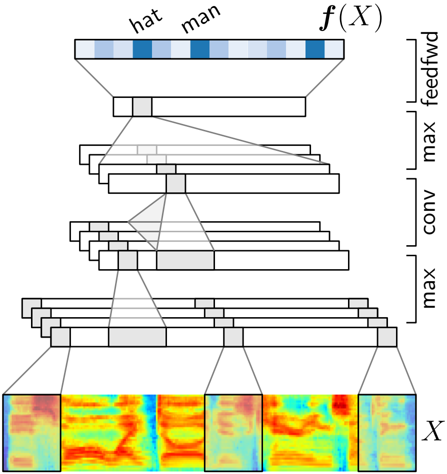


Word prediction from images and speech

$\boldsymbol{f}(X) \in \mathbb{R}^W$ is vector of word probabilities



Word prediction from images and speech

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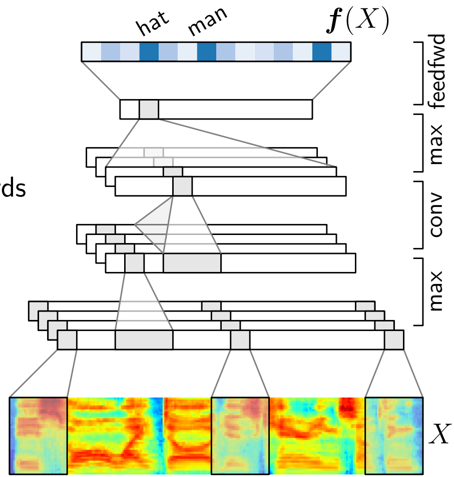
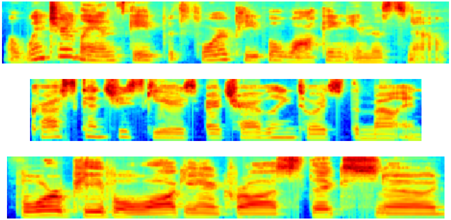
I.e., a spoken bag-of-words (BoW) classifier



Images paired with untranscribed speech

We are still in this setting:



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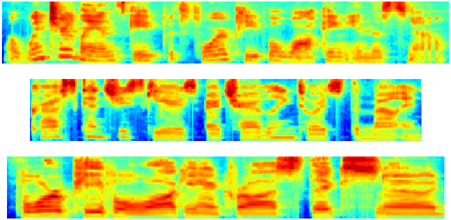

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- But our resulting model can make bag-of-words (BoW) predictions
- Note: Vision system could be seen as language independent (future)

Experimental details

- **Data:** 8000 images with 5 spoken captions, divided into train, development and test sets [Harwath and Glass, ASRU'15]
- **Prediction:** Output words w where $f_w(X) > \alpha$
- **Tasks:** Spoken bag-of-words prediction; keyword spotting
- **Evaluation:** Compare to words in transcriptions of test data

Task 1: Spoken bag-of-words prediction

Input utterance	Predicted BoW labels
Play	

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man on bicycle is doing tricks in an old building	**bicycle**, bike, **man**, riding, wearing

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Input utterance	**Predicted BoW labels**
man on bicycle is doing tricks in an old building	**bicycle**, bike, **man**, riding, wearing
a little girl is climbing a ladder	child, **girl**, **little**, young
a rock climber standing in a crevasse	climbing, man, **rock**
a dog running in the grass around sheep	**dog**, field, **grass**, **running**
a man in a miami basketball uniform looking to the right	ball, **basketball**, **man**, player, **uniform**, wearing

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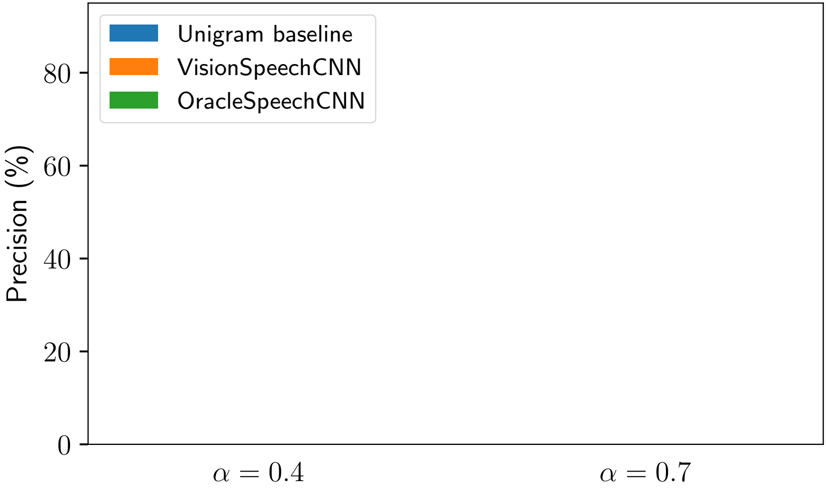

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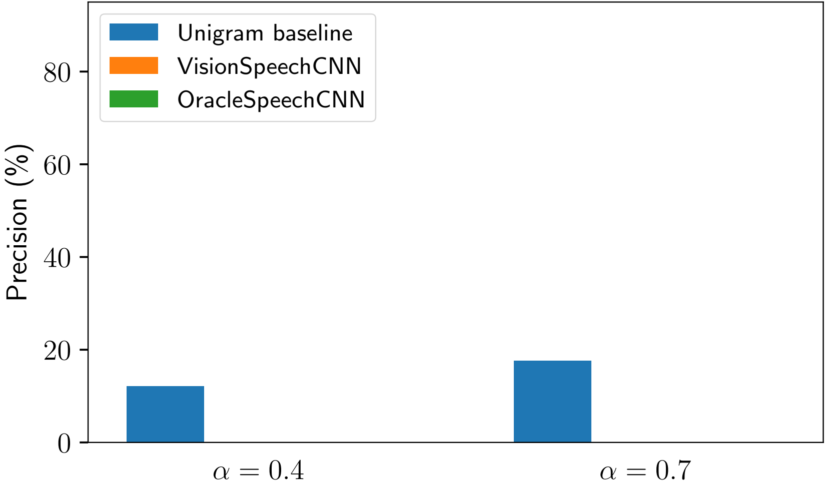

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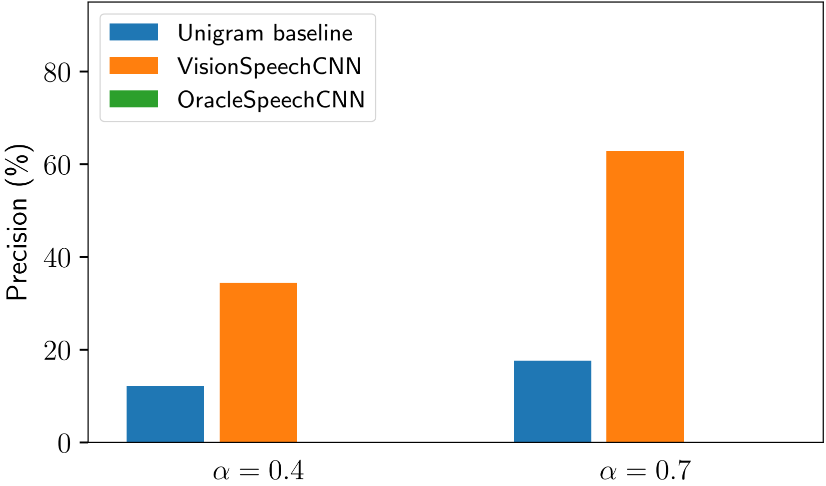

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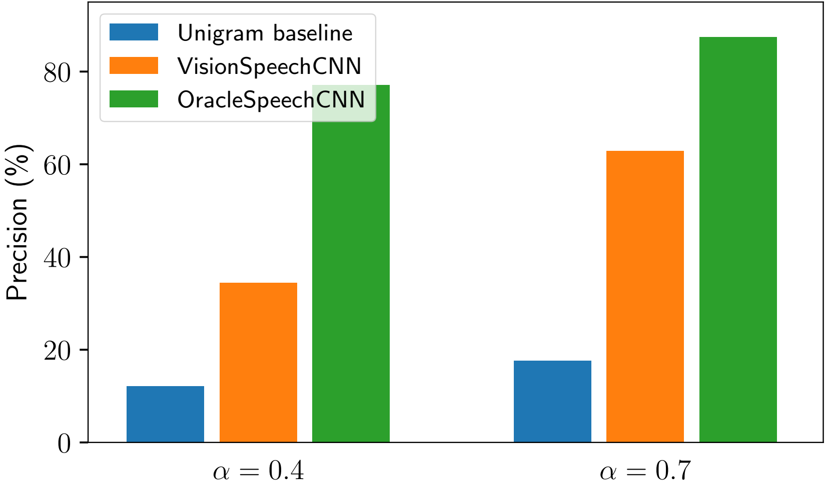

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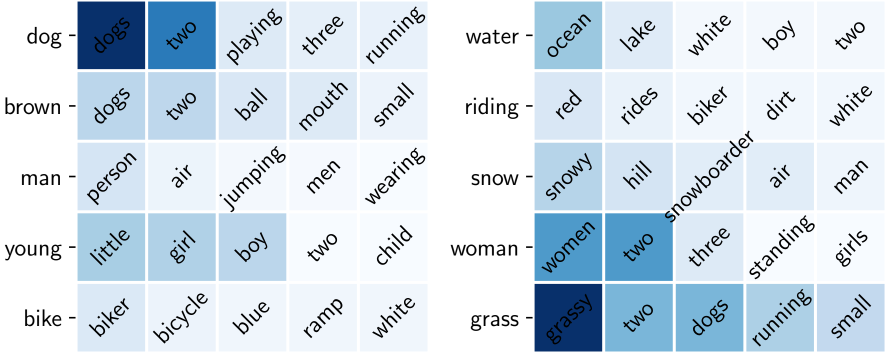

Task 2: Keyword spotting

Keyword	Example of matched utterance	Type
beach	Play (one of top 10)	
behind		
bike		
boys		
large		
play		
sitting		
yellow		
young		

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play	children playing in a ball pit	variant
sitting	two people are seated at a table with drinks	semantic
yellow	a tan dog jumping over a red and blue toy	mistake
young	a little girl on a kid swing	semantic

Task 2: Keyword spotting

Model	$P@10$	$P@N$	EER
Unigram baseline	5.0	3.5	50.0
VisionSpeechCNN	54.5	33.1	22.3
OracleSpeechCNN	96.5	83.0	4.1

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Future work coming, formalising this task.

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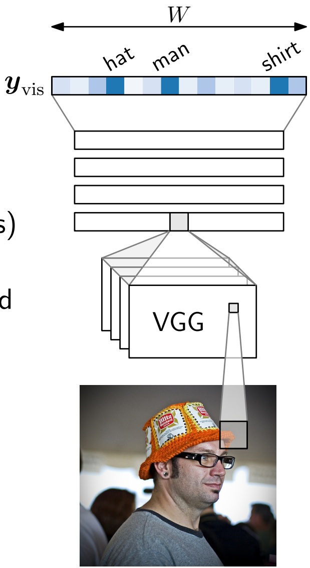
- Future: Thorough analysis of VisionSpeech models to see if they learn something about semantics; multi-lingual aspects
- What can we learn about language acquisition in humans?
- Language acquisition in robots

https://github.com/kamperh/recipe_vision_speech_flickr

The vision tagging system

- VGG-16 input layers (1.3M images)
  [Simonyan and Zisserman, arXiv'14]
- Train on Flickr30k (caption BoW labels)
- Targets: $W = 1000$ most common word types after removing stop words
- Note: Vision system could be seen as language independent (future work)



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$$L(\boldsymbol{f}(X), \boldsymbol{y}_{\text{vis}}) = -\sum_{w=1}^{W} \left\{ y_{\text{vis},w} \log f_w(X) + (1 - y_{\text{vis},w}) \log \left[1 - f_w(X)\right] \right\}$$

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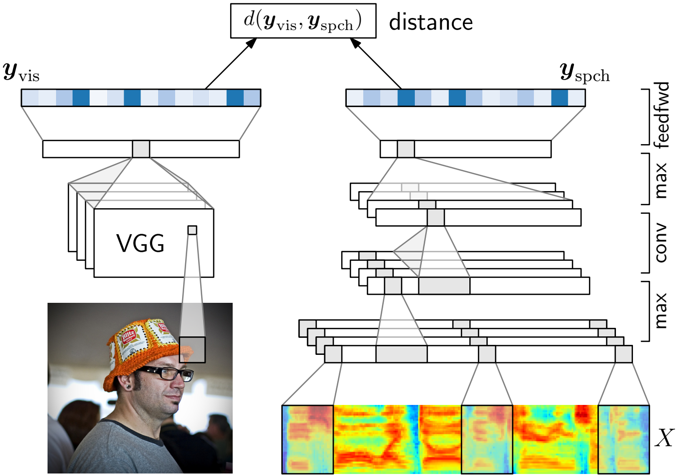
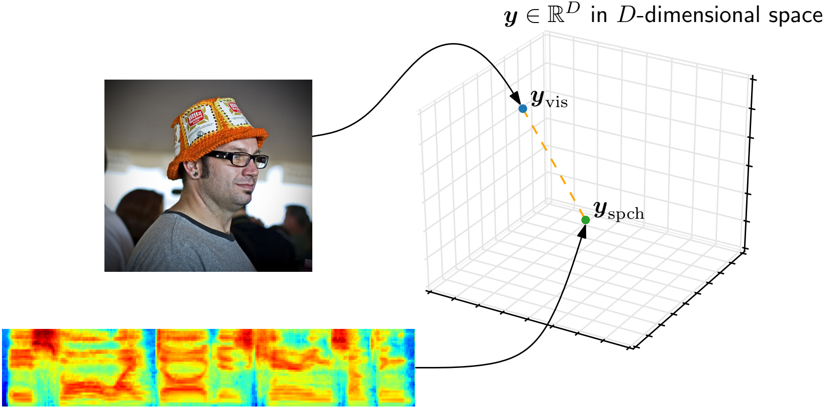
If $y_{\text{vis},w} \in \{0, 1\}$, this is summed log loss of W binary classifiers.

Map images and speech into common space



[Harwath et al., NIPS'16]

Retrieval in common (semantic) space



[Harwath et al., NIPS'16]

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