Deep convolutional acoustic word embeddings using word-pair side information

Herman Kamper[1], Weiran Wang[2], Karen Livescu[2]

[1]CSTR and ILCC, School of Informatics, University of Edinburgh, UK
[2]Toyota Technological Institute at Chicago, USA

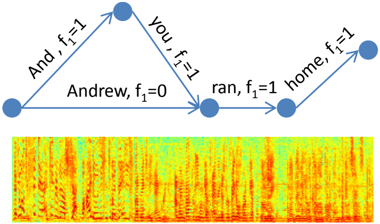
ICASSP 2016

Introduction

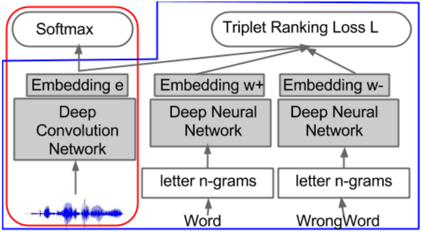
- Most speech processing systems rely on deep architecture to classify speech frames into subword units (HMM triphone states).
- Requires pronunciation dictionary for breaking words into subwords; in many cases still make frame-level independence assumptions.
- Some studies have started to reconsider whole words as basic modelling unit [Heigold *et al.*, 2012; Chen *et al.*, 2015].

Segmental automatic speech recognition

Segmental conditional random field ASR [Maas *et al.*, 2012]:



Whole-word lattice rescoring [Bengio and Heigold, 2014]:



Segmental query-by-example search

From [Levin *et al.*, 2015]:

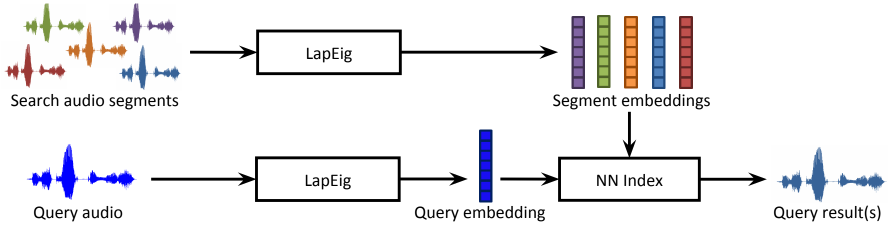


Fig. 1. Diagram of the S-RAILS audio search system.

[Chen *et al.*, 2015]: Similar scheme for "Okay Google" using LSTMs.

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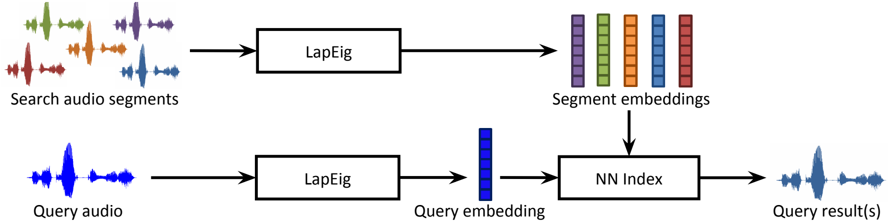

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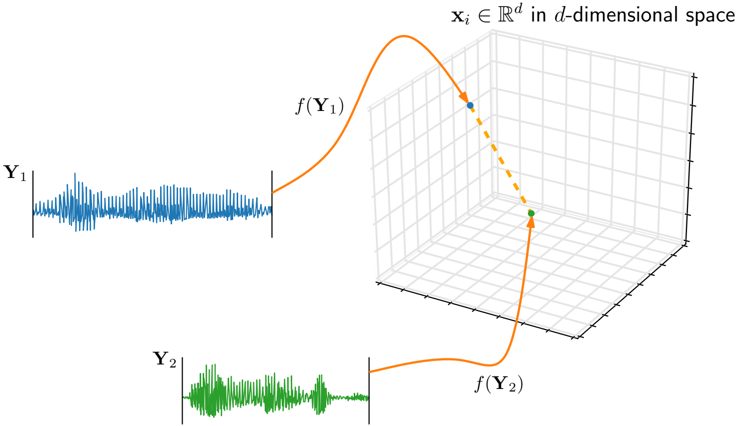
In this work, we also use a query-related task for evaluation.

Acoustic word embedding problem



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Segment we want to embed:

$\mathbf{y}_{t_1:t_2}$

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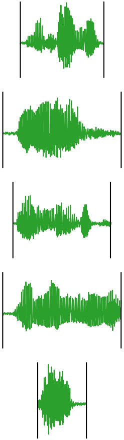
Reference set $\mathcal{Y}_{\text{ref}}$:



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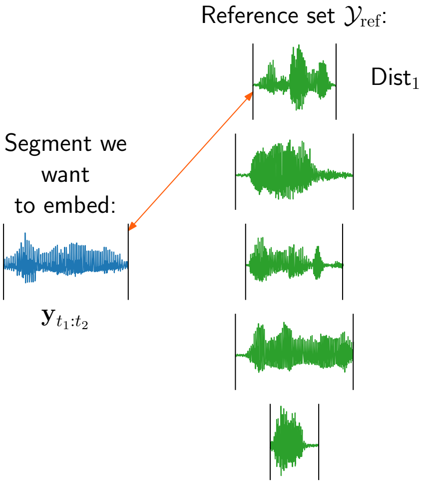

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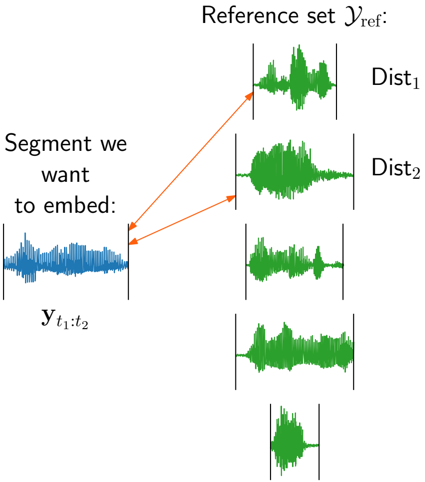

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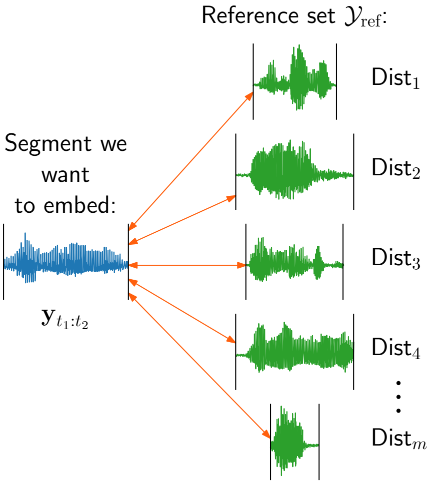

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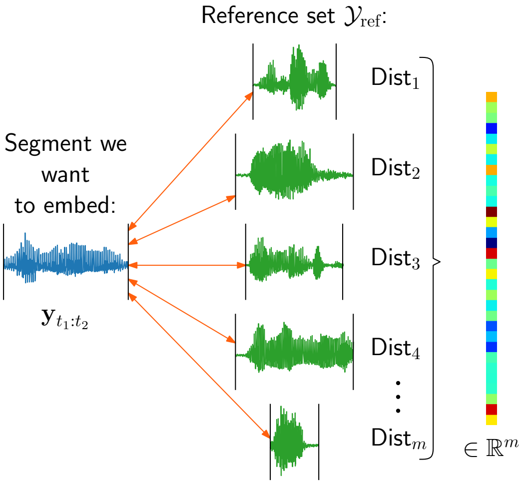

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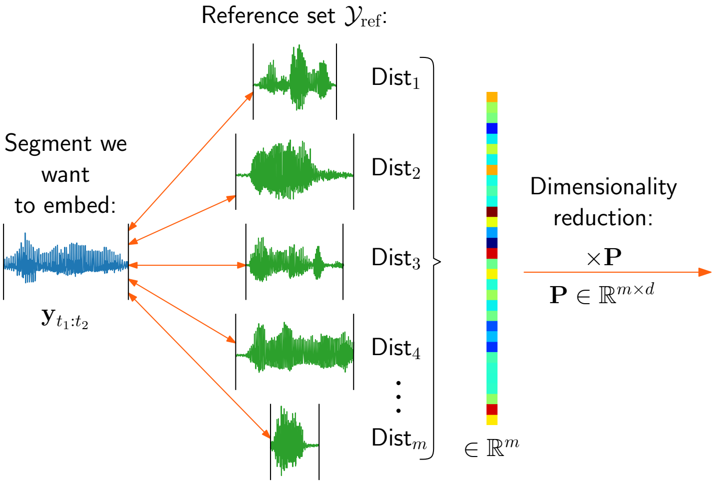

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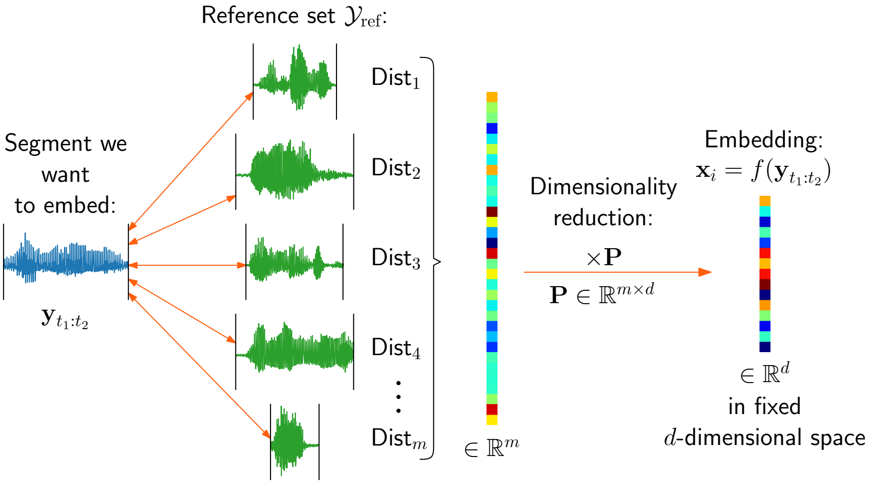

Word classification CNN [Bengio and Heigold, 2014]

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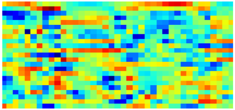
$$\overset{w_i}{\boxed{0\ 0\ 0\ \cdots\ 1\ \cdots\ 0\ 0}}$$



$\mathbf{Y}_i$

Word classification CNN [Bengio and Heigold, 2014]

softmax

w_i

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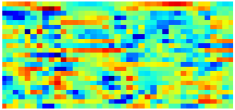

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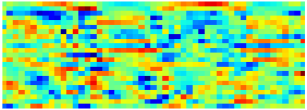

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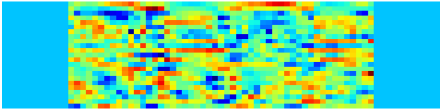

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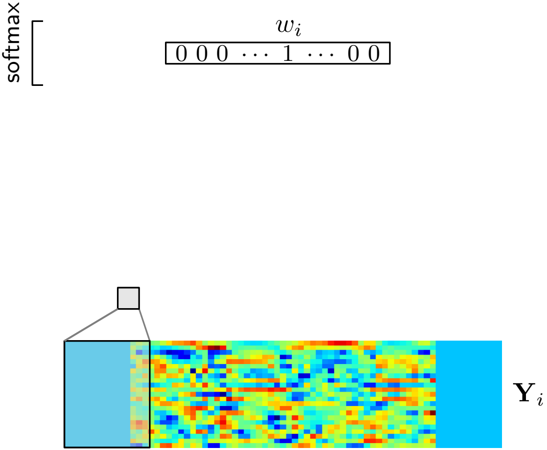

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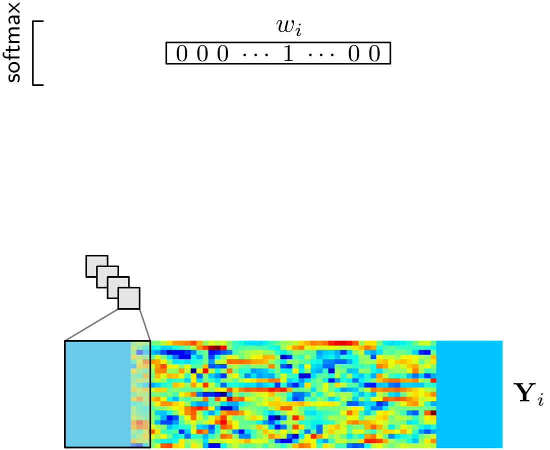

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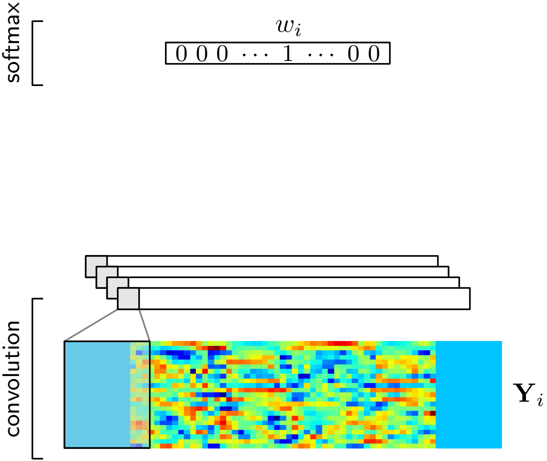

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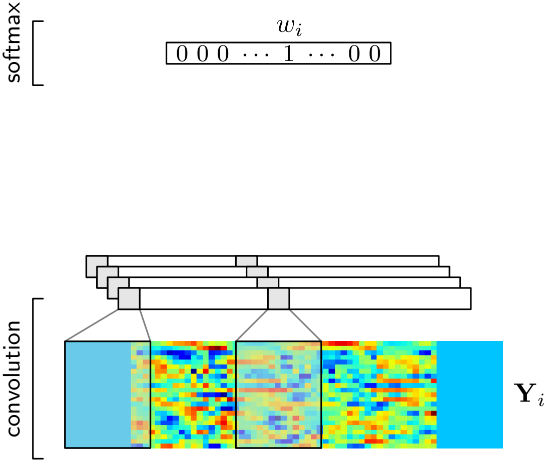

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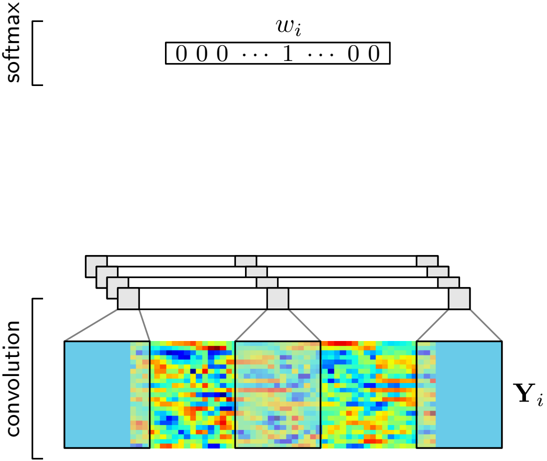

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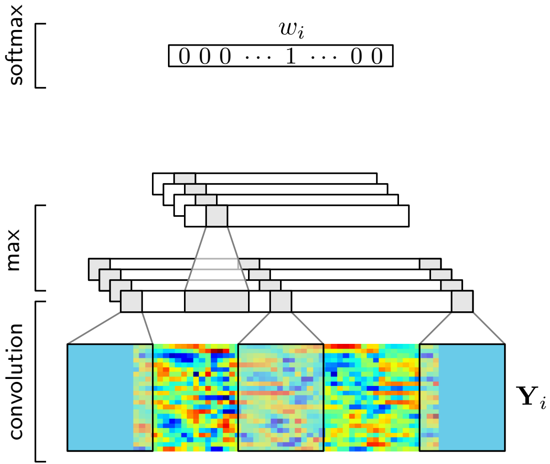

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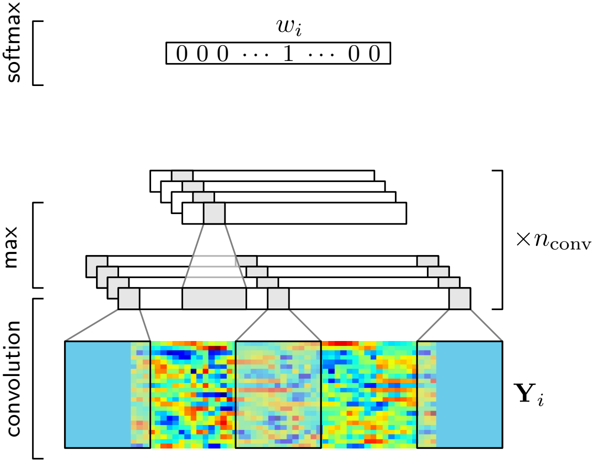

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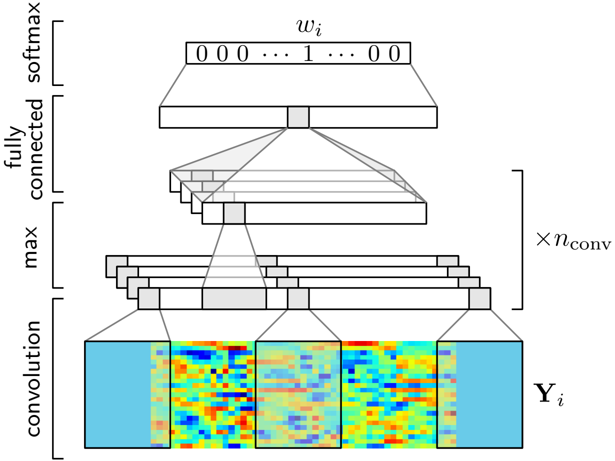

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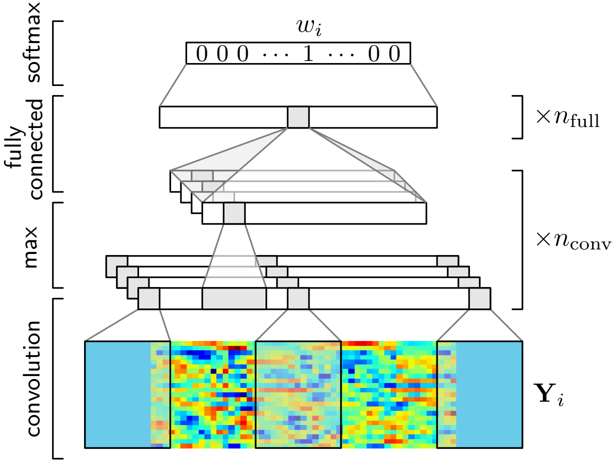

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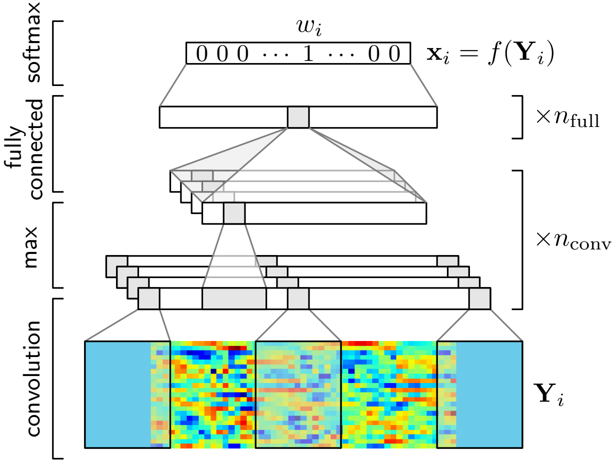

Supervision and side information

- The word classifier CNN assumes a corpus of labelled word segments.
- In some cases these might not be available.
- Weaker form of supervision we sometimes have (e.g. [Thiollière *et al.*, 2015]) are known word pairs: $\mathcal{S}_{\text{train}} = \{(m, n) : (Y_m, Y_n) \text{ are of the same type}\}$
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Can we use this weak supervision (sometimes called side information) to train an acoustic word embedding function f?

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Use idea of *Siamese networks* [Bromley *et al.*, 1993].

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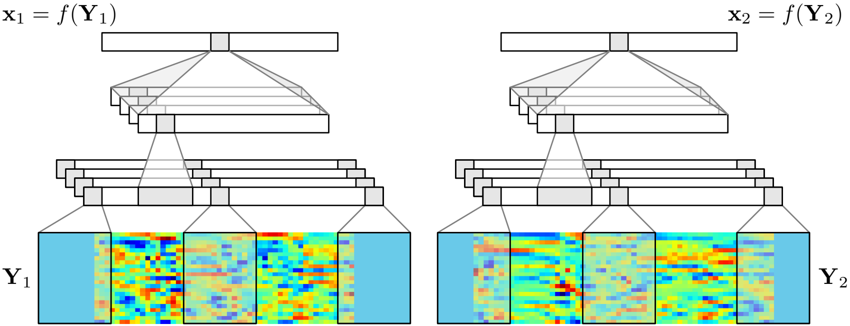

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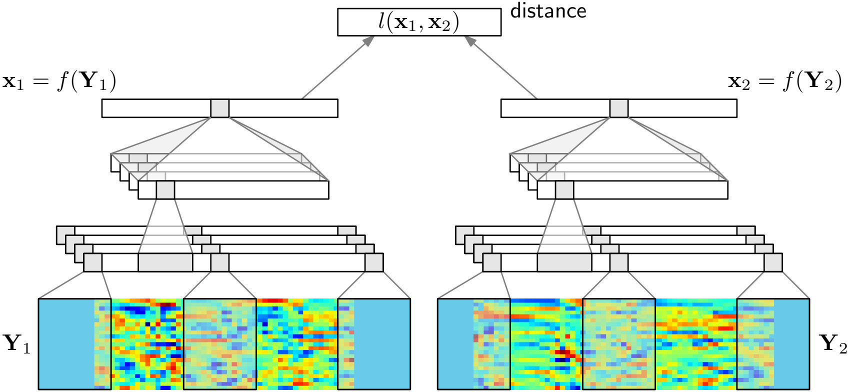

Loss functions

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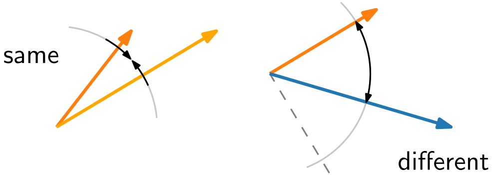
The coscos^2 loss [Synnaeve *et al.*, 2014]:

$$l_{\cos\ \cos^2}(\mathbf{x}_1, \mathbf{x}_2) = \begin{cases} \frac{1-\cos(\mathbf{x}_1,\mathbf{x}_2)}{2} & \text{if same} \\ \cos^2(\mathbf{x}_1, \mathbf{x}_2) & \text{if different} \end{cases}$$



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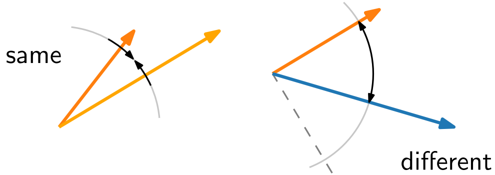

Margin-based hinge loss [Mikolov, 2013]:

$$l_{\cos\ \text{hinge}} = \max\left\{0, m + d_{\cos}(\mathbf{x}_1, \mathbf{x}_2) - d_{\cos}(\mathbf{x}_1, \mathbf{x}_3)\right\}$$

where $d_{\cos}(\mathbf{x}_1, \mathbf{x}_2) = \frac{1-\cos(\mathbf{x}_1,\mathbf{x}_2)}{2}$ is the cosine distance between $\mathbf{x}_1$ and $\mathbf{x}_2$, and m is a margin parameter. Pair $(\mathbf{x}_1, \mathbf{x}_2)$ are same, $(\mathbf{x}_1, \mathbf{x}_3)$ are different.

Embedding evaluation: the same-different task

Proposed in [Carlin *et al.*, 2011] and also used in [Levin *et al.*, 2013].

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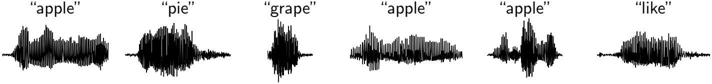

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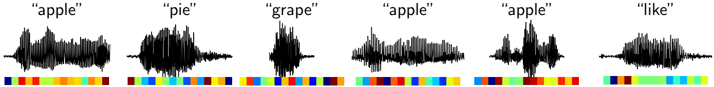

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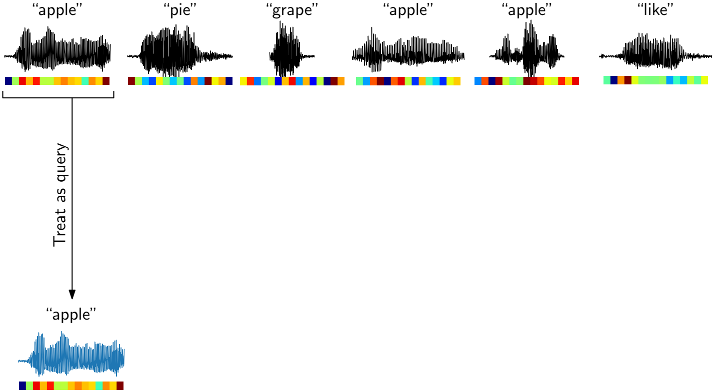

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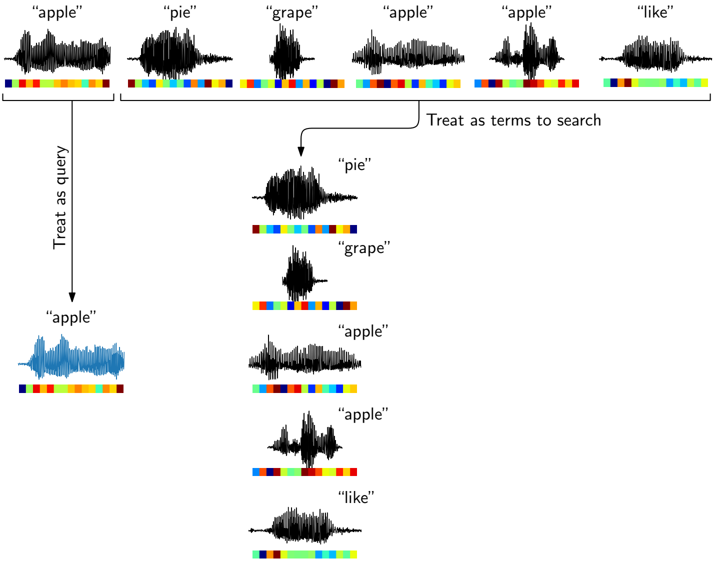

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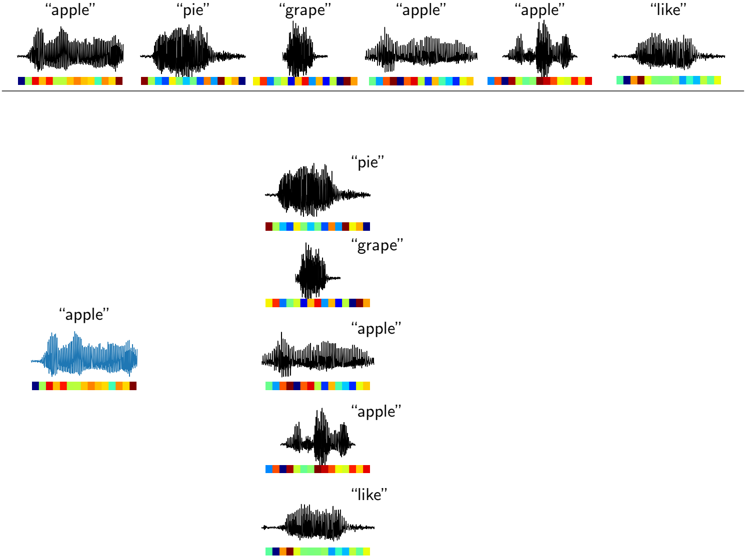

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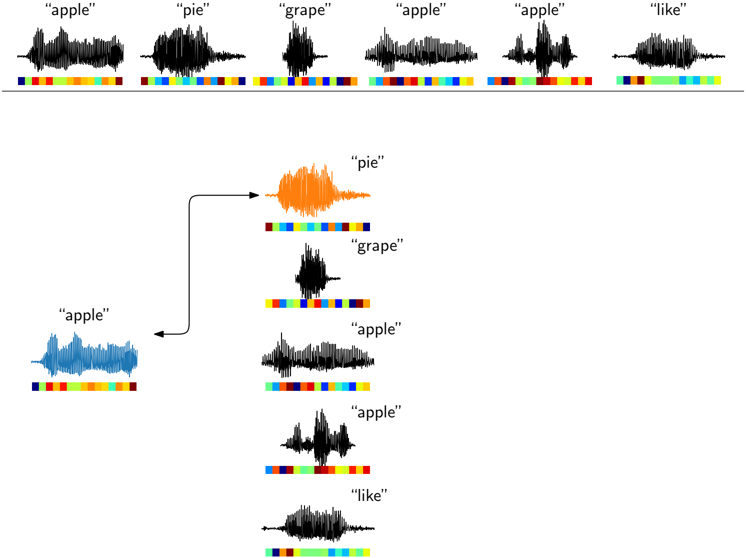

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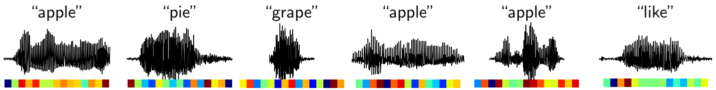

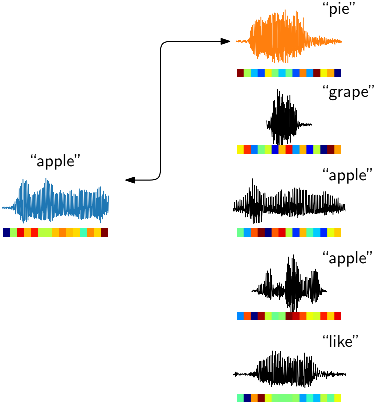

Cosine distance:	$d_i <$ threshold? predict:
d_1	

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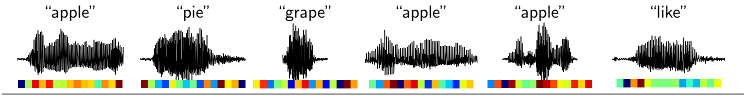

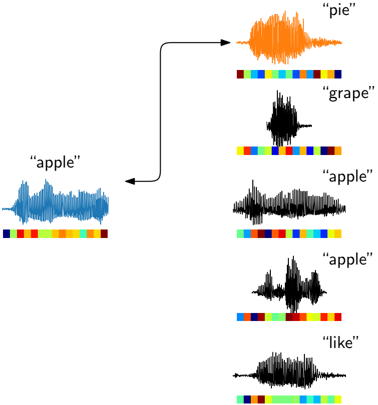

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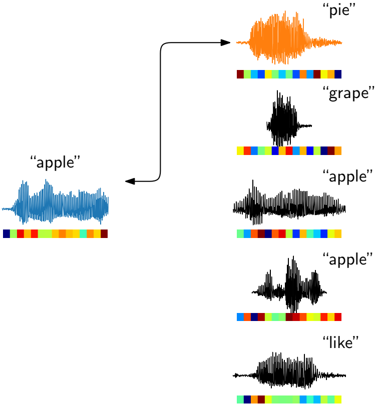

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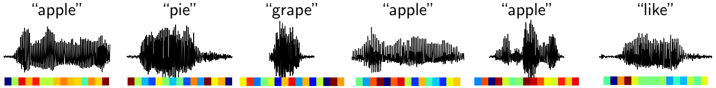

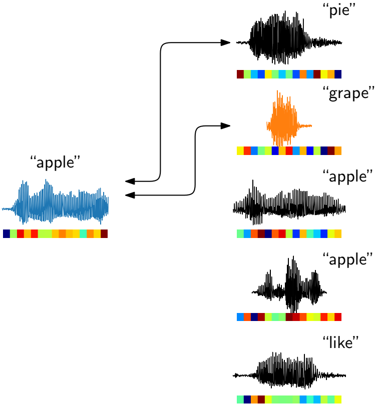

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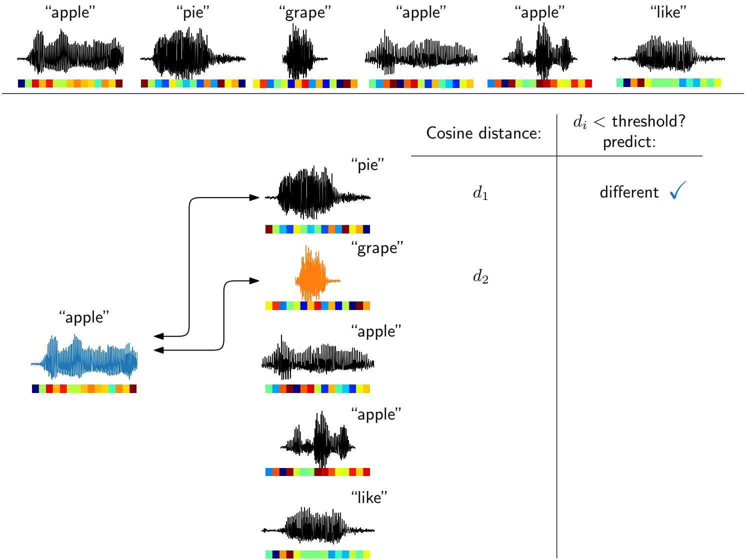

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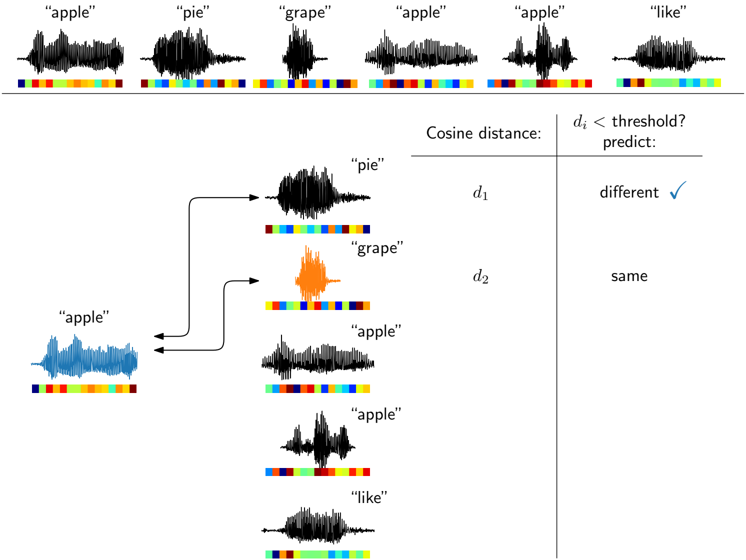

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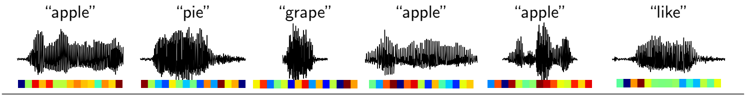

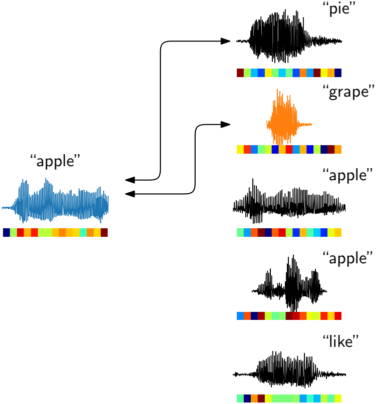

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d_1	different ✓
d_2	same ×

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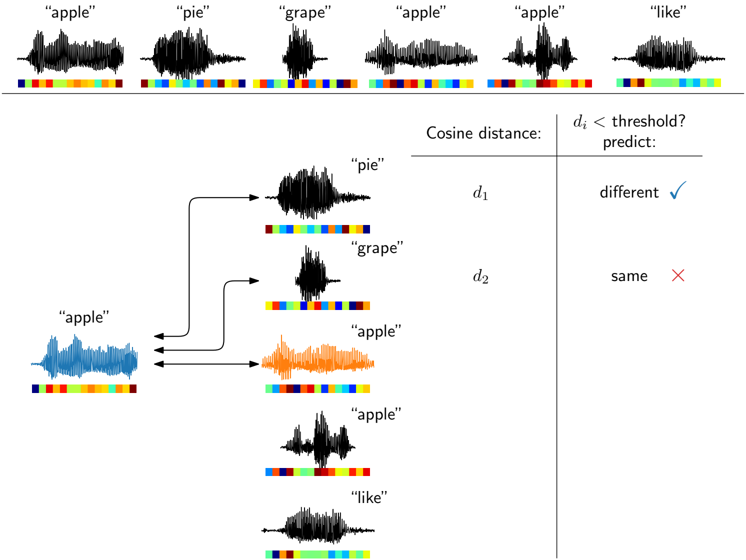

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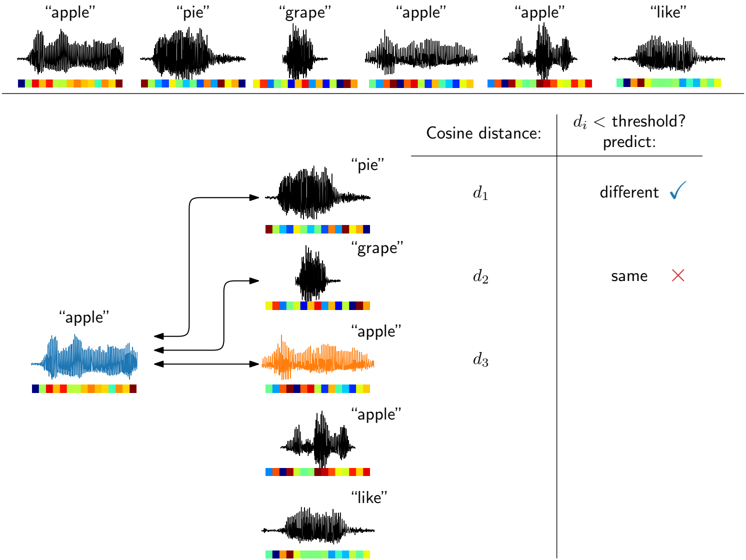

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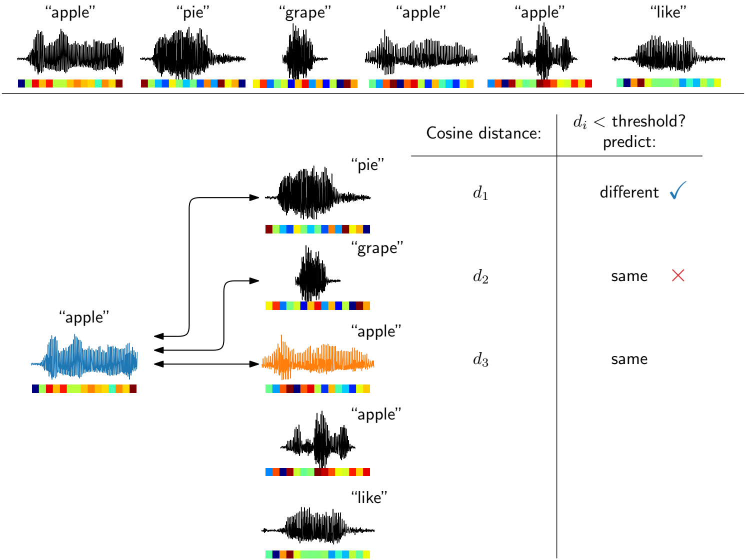

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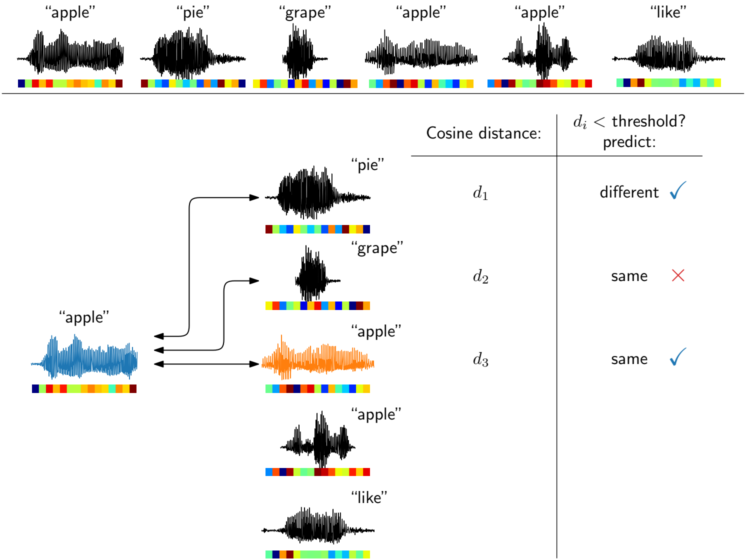

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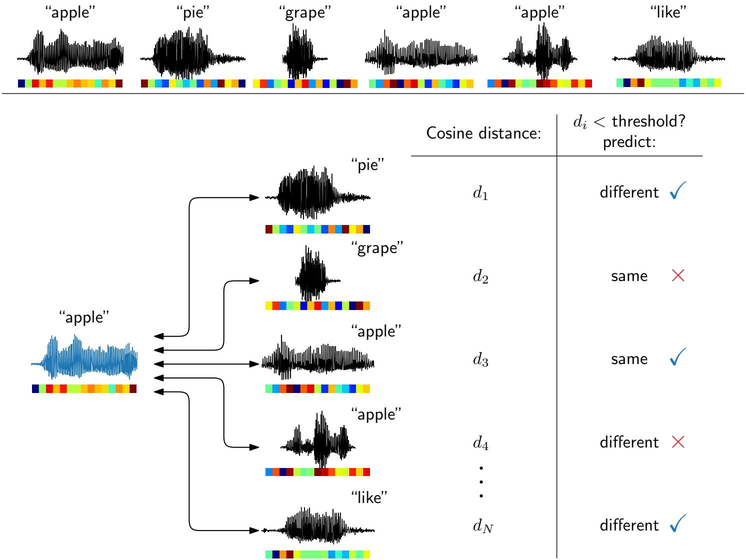
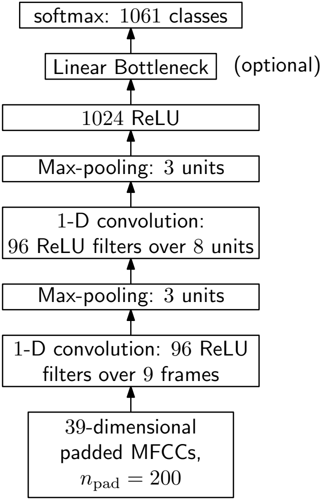


Experimental setup

- Speech from Switchboard is used for evaluation.
- Training set: 10k word tokens; sampled 100k training word pairs.
- Test set for same-different evaluation: 11k word tokens, 60.7M pairs, 3% produced by same speaker.
- Used a comparable development set.

Network architectures: Word classifier CNN



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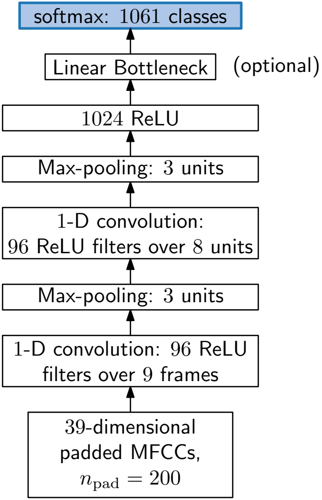

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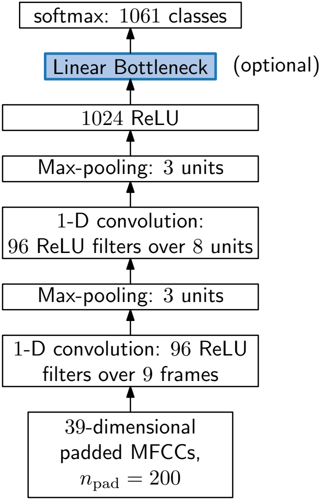
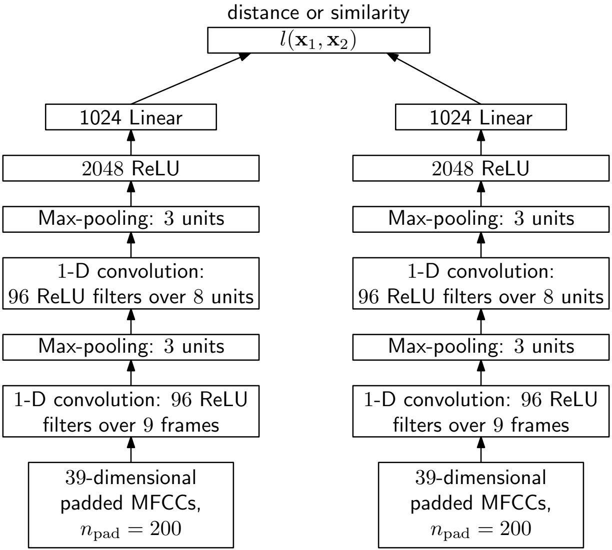


Network architectures: Siamese CNN



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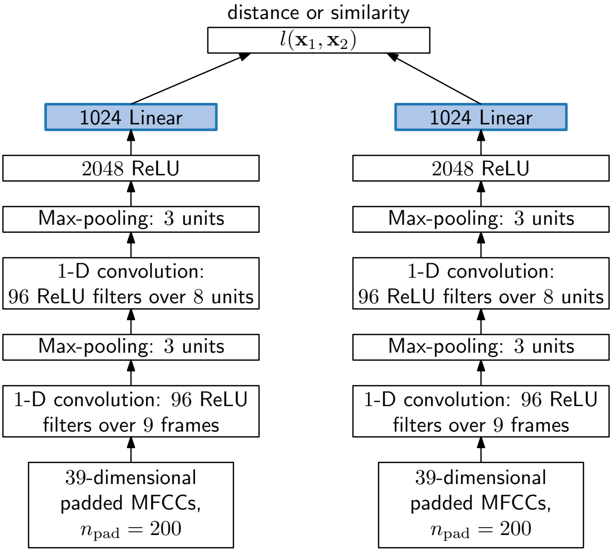

Results

Representation	Dim	AP

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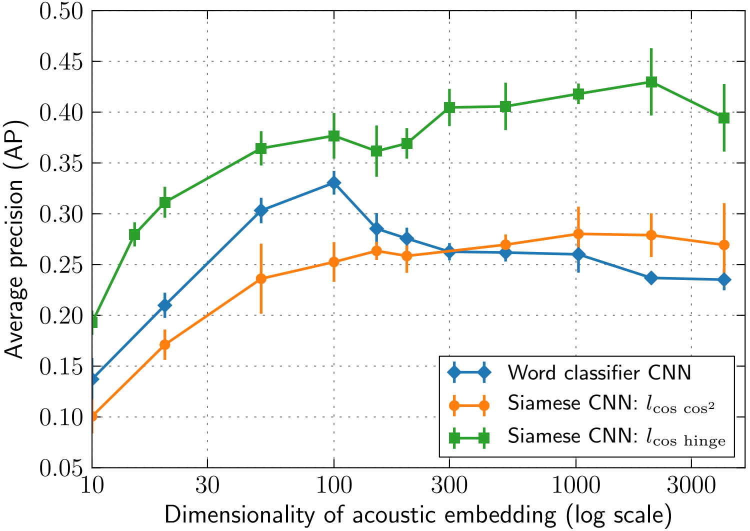
		50	0.504 ± 0.011
	LDA on: $l_{\text{cos hinge}}$, $d = 1024$	100	0.545 ± 0.011

Varying dimensionalities on development data



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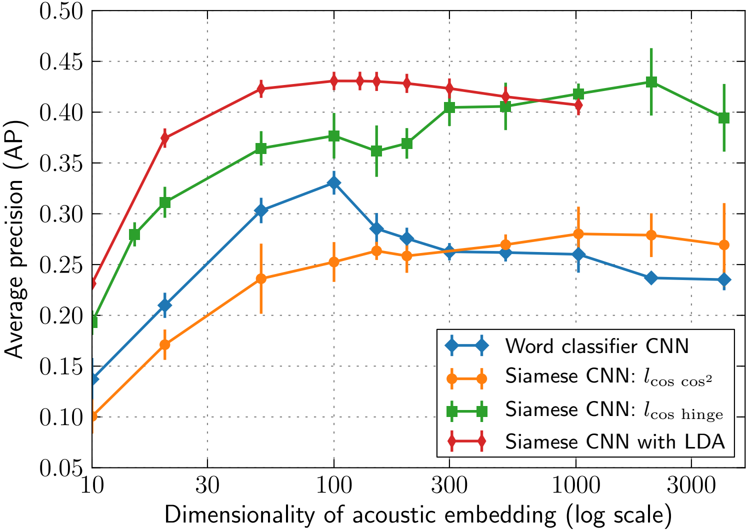

Summary and conclusion

- Introduced the Siamese CNN for obtaining acoustic word embeddings, and evaluated different cost functions.
- Evaluated using word discrimination task, and showed similar performance to word classifier CNN.
- For smaller dimensionalities: Siamese CNN outperformed classifier CNN.
- Self-criticism: evaluated on a small dataset (low-resource setting).
- Future work: sequence models, using embeddings for search and ASR.

Code

Neural networks (Theano): `https://github.com/kamperh/couscous`

Complete recipe: `https://github.com/kamperh/recipe_swbd_wordembeds`