Sampling strategies in Siamese Networks for unsupervised speech representation learning

Rachid Riad, Corentin Dancette, Julien Karadayi, Neil Zeghidour, Thomas Schatz, Emmanuel Dupoux

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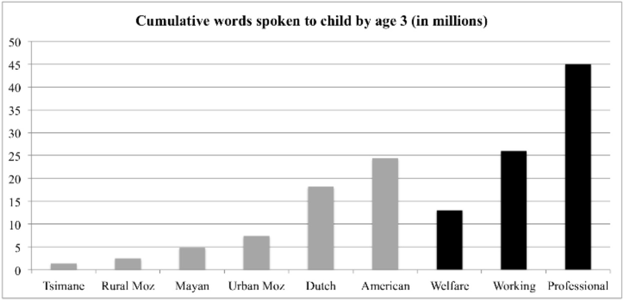
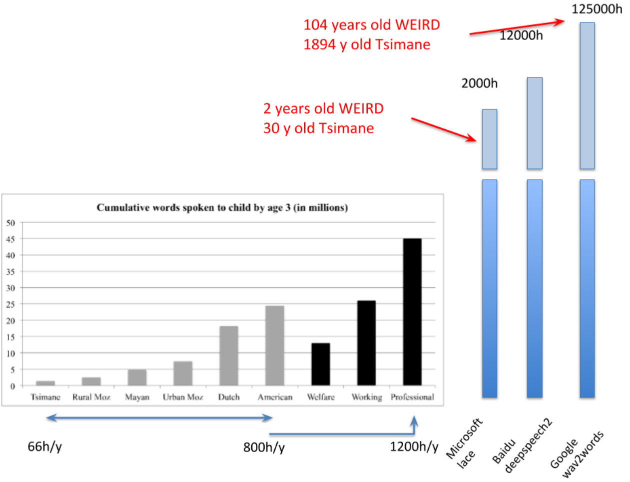
Outline

Introduction



[Cristia et al., 2017]

Introduction



[Cristia et al., 2017]

Current limits of ASR systems

Human parity for speech recognition

[Xiong et al., 2016] Microsoft claims to achieve human parity

- 2000+ hours of transcribed speech to train acoustic model
- 350M+ words to train the language model

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Too expensive and time consuming to gather these data for most languages.

Zero-resource Challenge 2015

Goal of the challenge

Unsupervised discovery of linguistic units, with two tracks

Sub-word modelling

[s] [p] [o] [w] [k]

Spoken term discovery

“magret”, “table”, “the”

Zero-resource Challenge 2015

The Buckeye dataset

- Casual conversations of English
- 12 speakers
- 5 hours of datasets, 16-30 min for each speaker

The Mboshi dataset

- Read speech of Mboshi, a Bantu language from Congo
- 24 speakers
- 2.5 hours of datasets, 2-29 min for each speaker

Zero-resource Challenge 2015

Track 1 : Sub-word modelling

- **Highlight** relevant linguistic properties : **phone** structure
- **Downplay** irelevant linguistic properties : **ID, channel, etc.**

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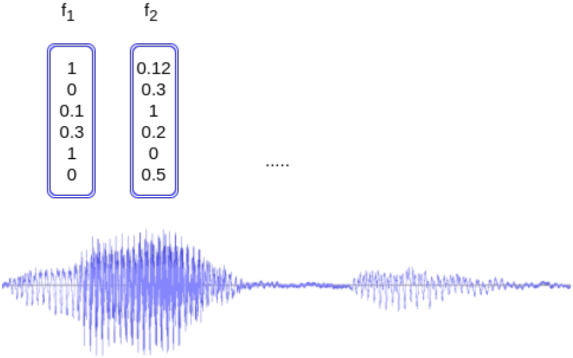
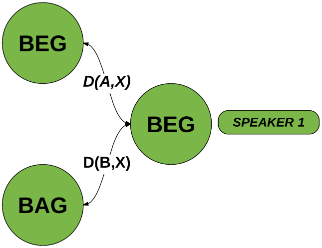


Zero-resource Challenge

Evaluation : ABX discriminability task [Schatz et al., 2013]

- Triplet A, B and X with A and X in the same phonetic class
- $D(A, X) < D(B, X)$ success 1, failure otherwise
- Average over all possible triplets



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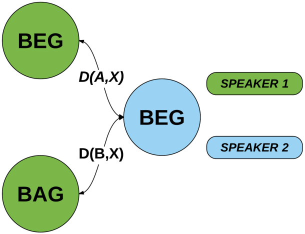
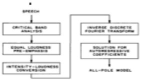


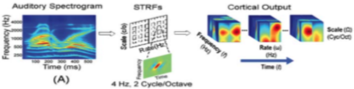
Unsupervised sub-word modelling

- Acoustic features
  PLP, RASTA



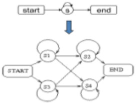
Hermanky (1990). *JASA*

- Auditory model



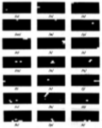
Chi, Ru, & Shamma (2005) *JASA*

- HMM state splitting



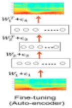
Varadarajan, Khudanpur,Dupoux, (2008)

- Kohonen's maps



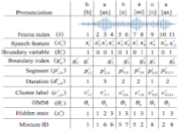
Kohonen (1988), *Computer*

- Deep autoencoders



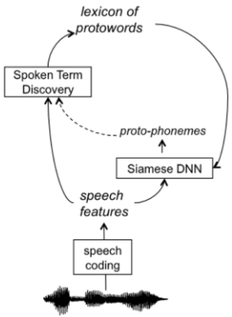
Badino, Canevari, et al (2014), *ICASSP*.

- Non Parametric Bayesian Clustering



Lee & Glass, (2012). *Proc of ACL*

Joint lexical-sublexical learning

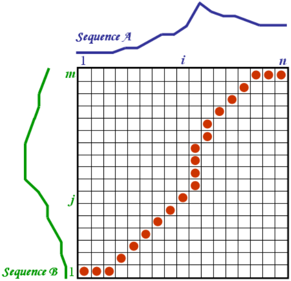


1. Discover words
2. Feed aligned frames of two words to the Siamese neural network

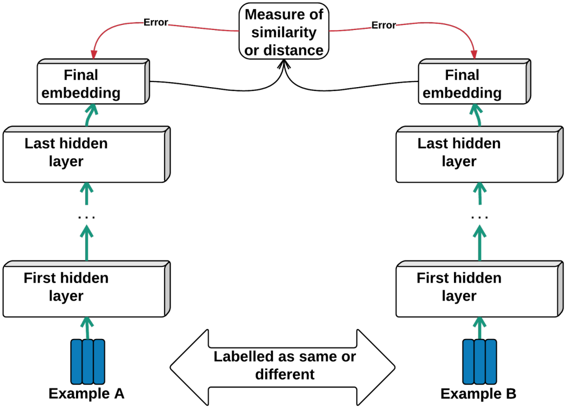
[Synnaeve et al., 2014, Thiollière et al., 2015, Dupoux, 2018]

Aligning a word pair with DTW

Dynamic Time Warping



Siamese Architecture



Loss function

Minimize distance of same discovered frames
Maximize distance of different discovered frames

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$$l_\gamma(x_1, x_2, y) = \begin{cases} -\cos(e(x_1), e(x_2)), & \text{if } y = 1 \\ \max(0, \cos(e(x_1), e(x_2)) - \gamma), & \text{otherwise} \end{cases}$$

Sampling Schema for pairs

How do we select training data for siamese network ?

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"the" "at"

Sampling Schema for pairs

How do we select training data for siamese network ?

"the"

"at"

"magret"

"table"

Sampling Schema for pairs

How do we select training data for siamese network ?

Previously in Siamese networks... [Thiollière et al., 2015]

- Randomly choosing two words in the dataset
- Balancing same / different pairs
- Balancing same / different speakers pairs

Sampling Schema for pairs

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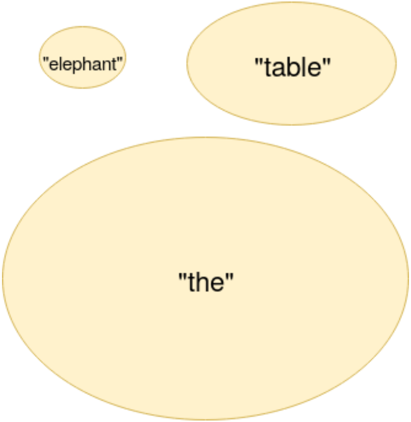
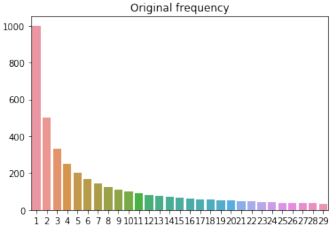
Parameters

- ϕ Distribution choice to sample words
- P_w^- Same versus Different word Ratio
- P_s^- Same versus Different Speaker Ratio

Word frequencies



Distribution follows an empirical power law : **Zipf's Law**. [Zipf, 1949]



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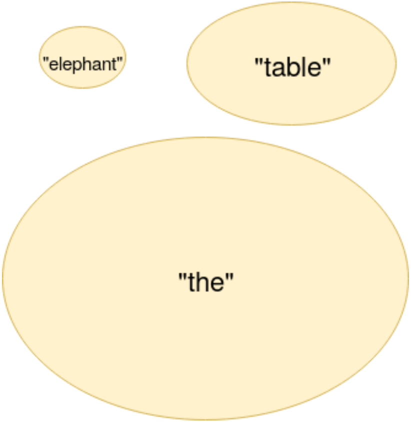

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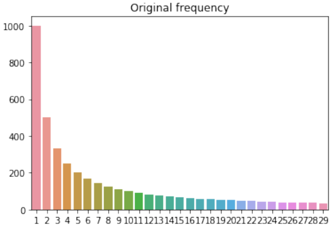

$$f_w \propto \frac{1}{r_w^{\alpha}}, \alpha \approx 1$$

Sampling compression function

Let say a word w as a number of occurrences n_w.
We define the sampling compression function Φ such as :

Sampling compression function

$$\mathbb{P}(w) = \frac{\phi(n_w)}{\sum\limits_{\forall w'} \phi(n_{w'})} \tag{1}$$

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[Mikolov et al., 2013, Levy et al., 2015]

Sampling compression functions

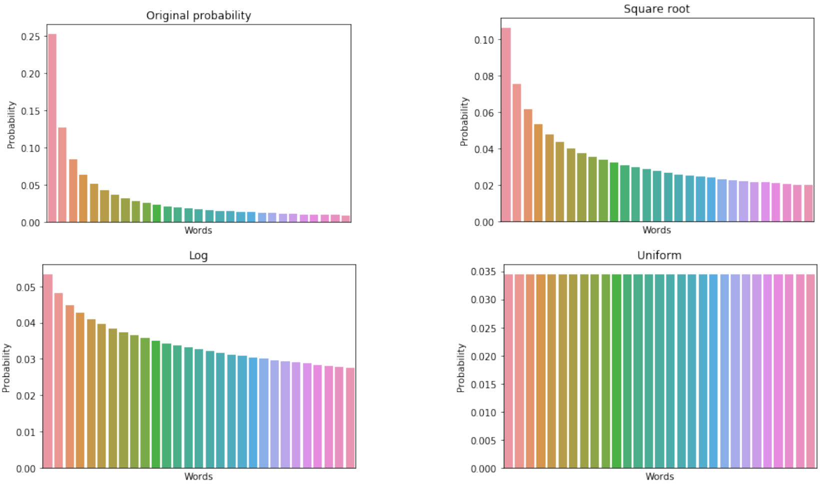
We evaluated 5 different sampling compression functions

Sampling functions Φ

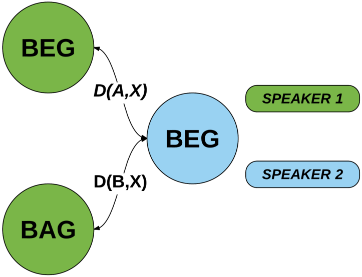
- $n \rightarrow n$
- $n \rightarrow \sqrt{n}$
- $n \rightarrow \sqrt[3]{n}$
- $n \rightarrow \log(1 + n)$
- $n \rightarrow 1$

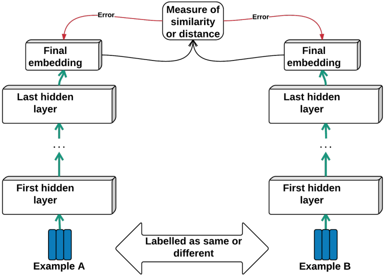
The objective is to balance the effect of Zipf's law on the sampling.

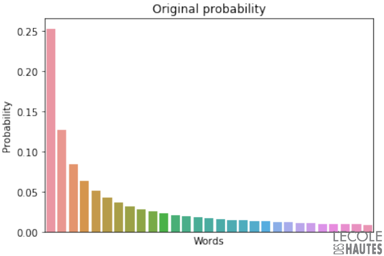
Sampling compression function



Summary of methods







Measure sampling contribution

Weakly-supervised setting

Lexical of real words as weak labels

Training

- 12 speakers from the Buckeye corpus, 5 hours
- Split in 4 different sizes

Evaluation on test set

- 2 other speakers from the Buckeye corpus

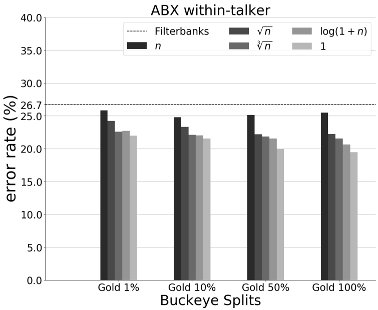
Weakly supervised setting

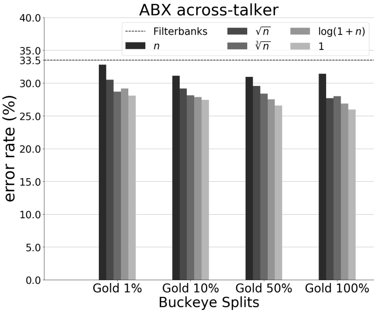
Table – Statistics for the 4 Buckeye splits used for the weakly supervised training, the duration in minutes expressed the total amount of speech for training

	Duration	#tokens	#words	#possible pairs
1%	3.0 min	1006	355	$\sim 5.10^5$
10%	29.9 min	7189	1297	$\sim 2.10^7$
50%	149.5 min	34912	3112	$\sim 6.10^8$
100%	299.1 min	69543	4538	$\geq 2.10^9$

Influence of Φ on results

Experience using gold words of buckeye.





It is beneficial to mitigate the effect on zipf's law on sampling.

Influence of the proportion of different-types pairs

What is the proportion P_w^- of negative pairs of words should we sample ?

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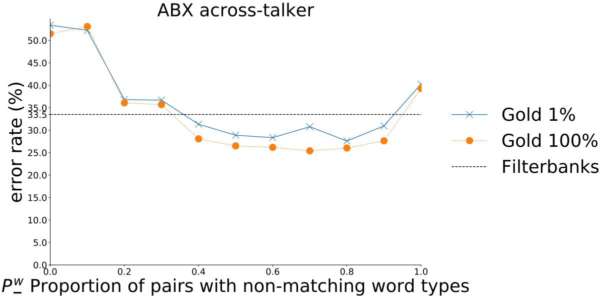

Influence of the proportion of different-speaker pairs

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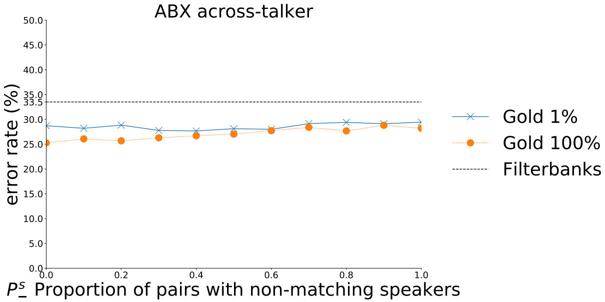


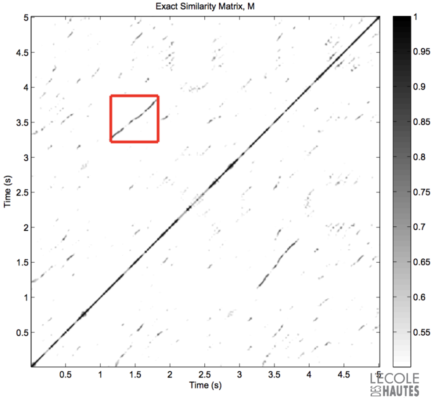
Parameters for best performance on weakly-supervised setting

1. $\phi : n \rightarrow 1$: **remove** the influence of word frequency
2. $P_w^- = 0.7$: **preference** for negative pairs (different words)
3. $P_s^- = 0$: **only** same-speaker pair

Unsupervised Spoken Term Discovery

[Jansen and Van Durme, 2011]

Discover words instead of using the labels of words.

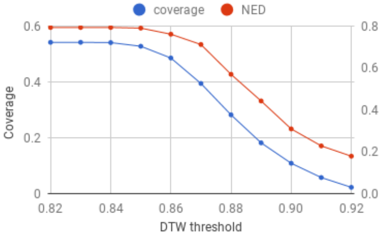


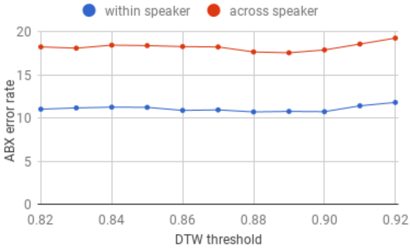
Test on zerospeech 2015 challenge

Table – ABX discriminability results for the ZeroSpeech2015 datasets. The best error rates for each conditions for siamese architectures are in **bold**. The best error rates for each conditions overall are underlined.

Models	English		Xitsonga	
	within	across	within	across
baseline (MFCC)	15.6	28.1	19.1	33.8
supervised topline (HMM-GMM)	12.1	16.0	04.5	03.5
Our ABnet with $P^{w}_{-} = 0.7, P^{s}_{-} = 0, \phi : n \rightarrow 1$	**10.4**	17.2	**9.4**	**15.2**
CAE [Renshaw et al., 2015]	13.5	21.1	11.9	19.3
ABnet [Thiollière et al., 2015]	12.0	17.9	11.7	16.6
ScatABnet [Zeghidour et al., 2016]	11.0	**17**	12.0	15.8
DPGMM [Chen et al., 2015]	10.8	16.3	9.6	17.2
DPGMM+PLP+bestLDA+DPGMM [Heck et al., 2016]	10.6	16.0	8.0	12.6

Spoken term discovery threshold





Conclusions

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Code in Python, pytorch

Code available online https://github.com/bootphon/abnet3

Next steps

Understand why using different-speaker pairs doesn't improve results

Fully unsupervised loop between Spoken Term Discovery and ABNet

Learn fixed-size representation of words and co-training with sub-word discriminative loss

Thank You!

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