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# A brief introduction to multichannel noise reduction with deep neural networks

Romain Serizel

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# A brief introduction to multichannel noise reduction with deep neural network.

Romain Serizel

LORIA, Université de Lorraine, Inria, CNRS (France)

Thursday 9<sup>th</sup>, January 2020



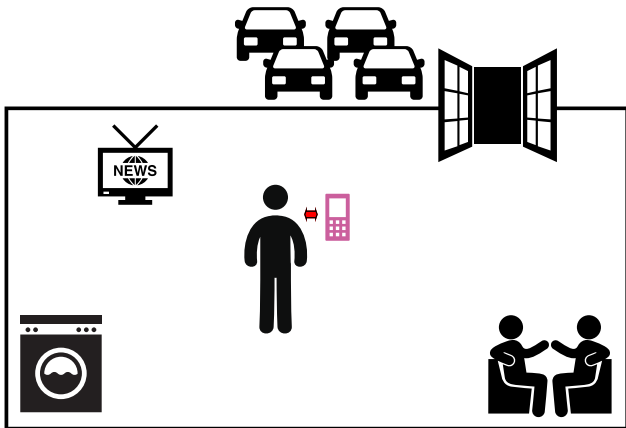
# Outline

- 1 Context and motivations
- 2 Multichannel speech enhancement
- 3 Introduction to artificial neural networks
- 4 DNN for multichannel speech enhancement
- 5 Conclusions and perspectives

# Speech in real conditions

Problem “solved”

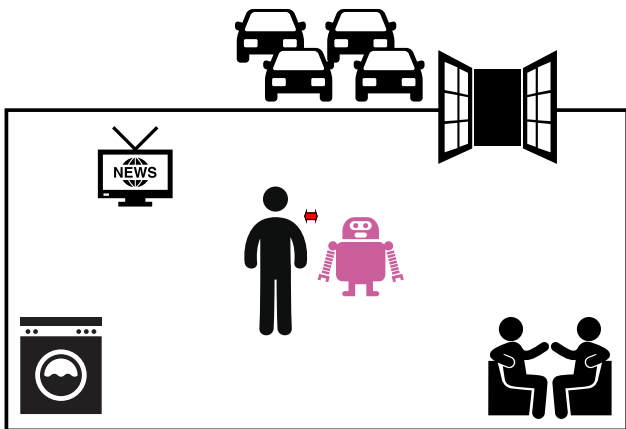
Close-up microphones, clean speech



# Speech in real conditions

There is some work to do :

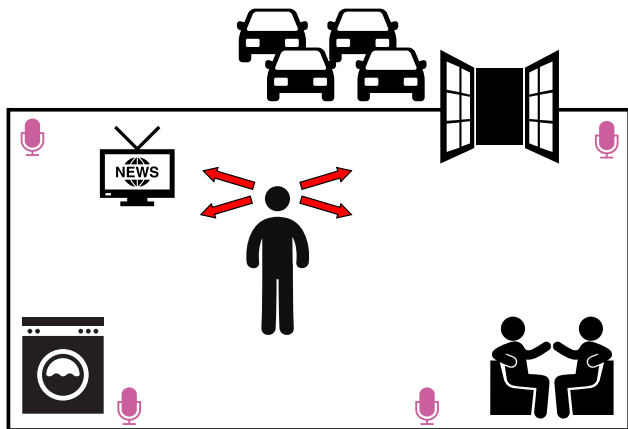
Moving microphones



# Speech in real conditions

There is some work to do :

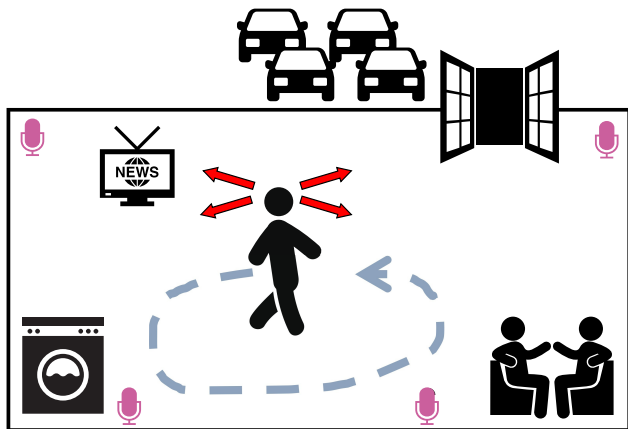
Distant microphones



# Speech in real conditions

There is some work to do :

Distant microphones, mobile sources...



# Multichannel speech enhancement ?

## Context

- Reduce the impact of the acoustic perturbations :
  - Cleaning the signal

## In this talk

- Focus on noise removal/attenuation
  - Noise reduction
  - Noise suppression
  - De-noising
  - ...



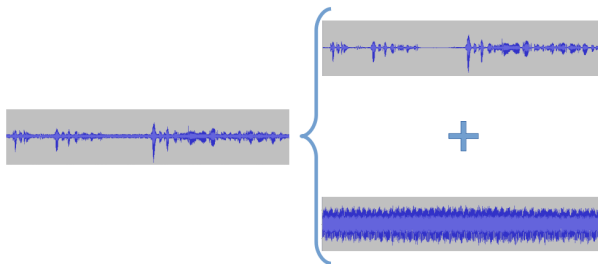
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# Signal model

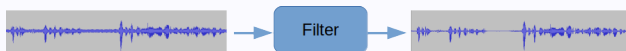
Signal observed

$$\mathbf{X} = \mathbf{X}_S + \mathbf{X}_N$$



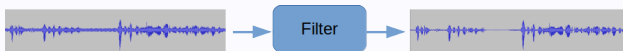
# Filtering

## Single-channel filter

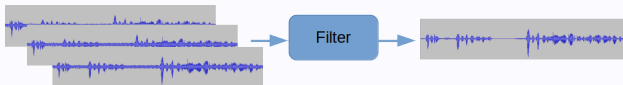


# Filtering

## Single-channel filter

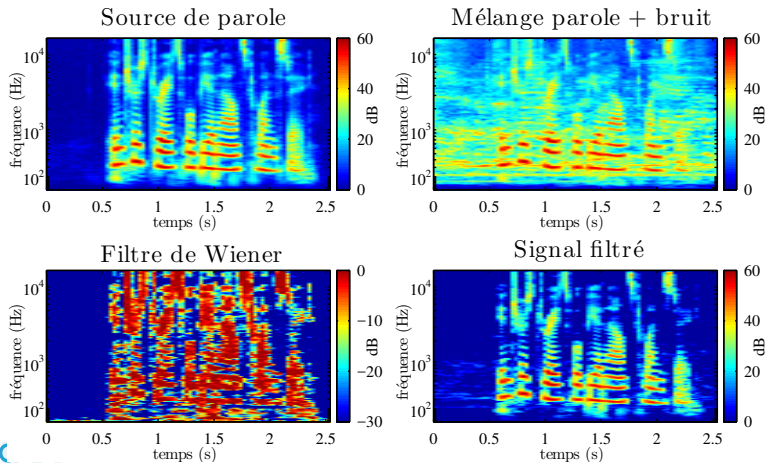


## Multichannel filter



# Single-channel enhancement

On single-mic data, perform spectral filtering/masking.



# Multichannel enhancement (1)

On multi-mic data, exploit spatial localization.

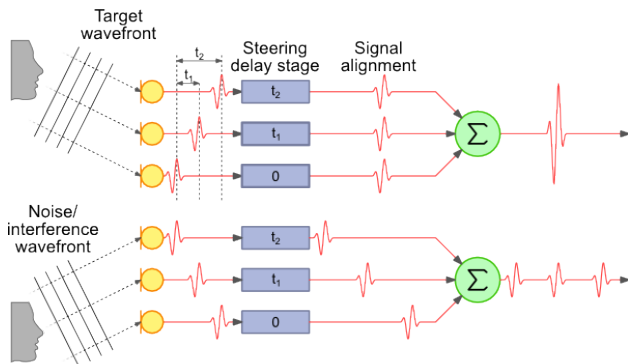
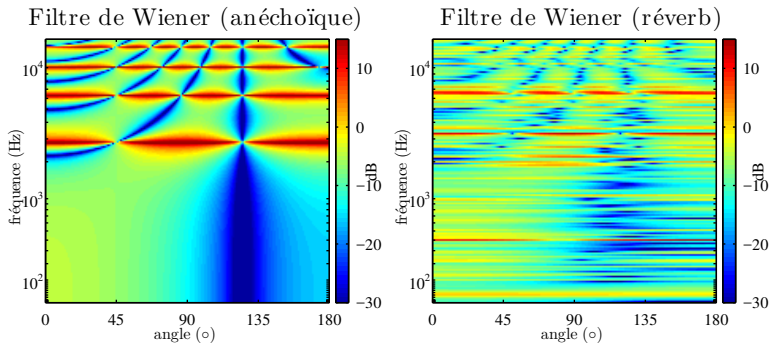


Image source : the lab book page

## Multichannel enhancement (2)

On multi-mic data, perform joint spatial and spectral masking.



# MWF-based speech enhancement (1)

## Speech distortion weighted MWF (MMSE criterion)

MMSE estimate of the (unknown) speech component :

$$\min_{\mathbf{W}} E\{|X_{\text{Ref}} - \mathbf{W}^H \mathbf{X}_s|^2\} + \mu\{\mathbf{W}^H \mathbf{X}_n|^2\}$$

## SDW-MWF

$$\mathbf{W} = (\mathbf{R}_s + \mu \mathbf{R}_n)^{-1} \mathbf{R}_s \mathbf{e}_{\text{Ref}}$$

- $\mathbf{X}_s, \mathbf{X}_n$  : speech, noise components of the microphone signals
- $\mathbf{W}^H \mathbf{X}$  : output signal of the filter  $\mathbf{W}$
- $\mathbf{R}_s$  and  $\mathbf{R}_n$  : speech and noise correlation matrices



## MWF-based speech enhancement (2)

### Estimation of the speech correlation matrix

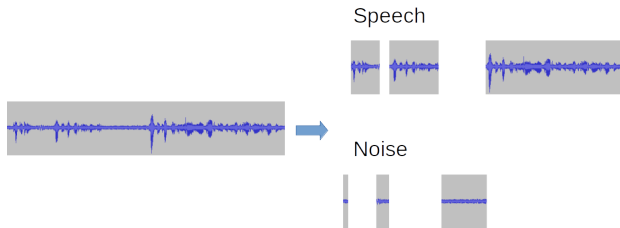
$\mathbf{R}_s$  is estimated from speech+noise correlation matrix  $\mathbf{R}_x$

and noise correlation matrix  $\mathbf{R}_n$  :

$$\mathbf{R}_s = \mathbf{R}_x - \mathbf{R}_n$$

→ Requires a voice activity detector !

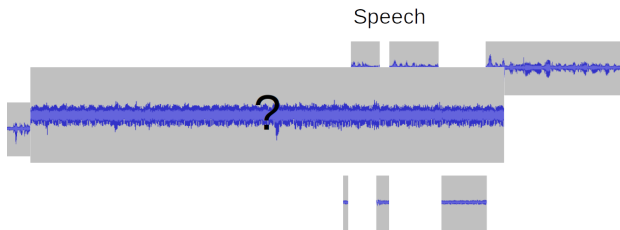
# Voice activity detector



## Limitations

- Limited to full frequency band
- Energy-based VAD do not work well at low SNR

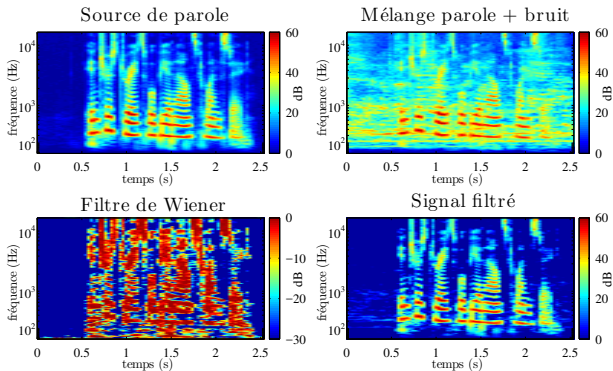
# Voice activity detector



## Limitations

- Limited to full frequency band
- Energy-based VAD do not work well at low SNR

# Time-frequency masks



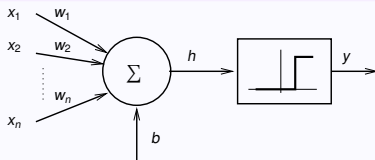
How can we obtain reliable masks ?

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# The perceptron 1

## Perceptron model



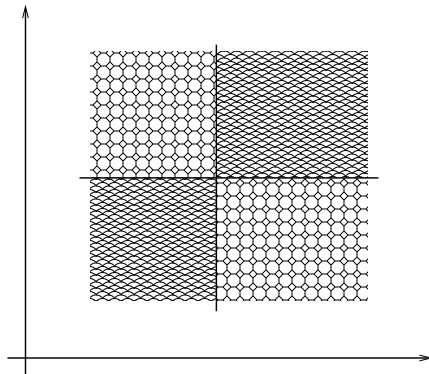
A perceptron is a linear classifier :

$$h = \mathbf{w} \cdot \mathbf{x} + b$$

$$y = f(h) \text{ e.g. } \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0 \\ 0 & \text{else} \end{cases}$$

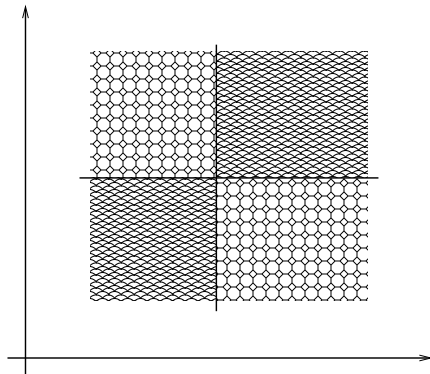
## The perceptron 2

Perceptron cannot model a  
XOR [Minsky *et al.*, 1969]  
⇒ Work on perceptron stopped



## The perceptron 2

Perceptron cannot model a  
XOR [Minsky *et al.*, 1969]  
⇒ Work on perceptron stopped



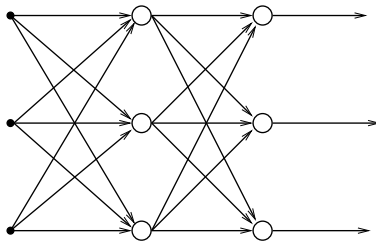
At least single perceptron cannot !



# Multilayer perceptrons

## Multilayer perceptrons (MLP) :

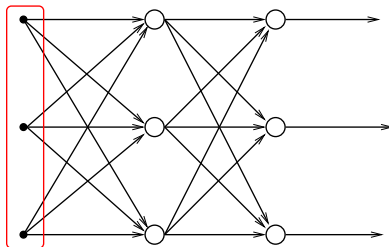
- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification



# Multilayer perceptrons

## Multilayer perceptrons (MLP) :

- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification

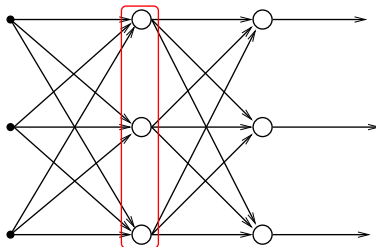


Input layer

# Multilayer perceptrons

## Multilayer perceptrons (MLP) :

- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification

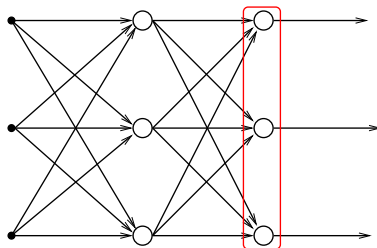


Hidden layer(s)

# Multilayer perceptrons

## Multilayer perceptrons (MLP) :

- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification

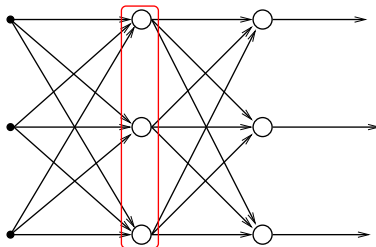


Output layer

# Multilayer perceptrons

## Multilayer perceptrons (MLP) :

- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification

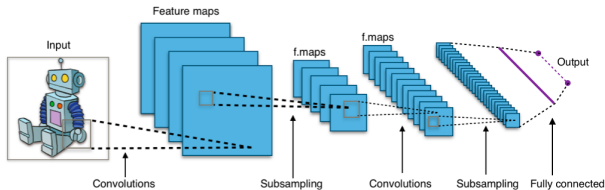


Deep neural networks have more than 1 hidden layers

# Convolutional neural networks (CNN)

## Keys ideas

- Detect patterns in images/spectrograms
- Apply sets of filters to obtain feature maps
- Subsample to control dimensionality

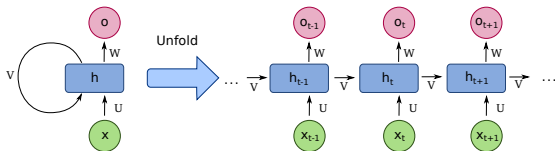


• Image source : wikimedia

# Recurrent neural networks (RNN)

## Keys idea

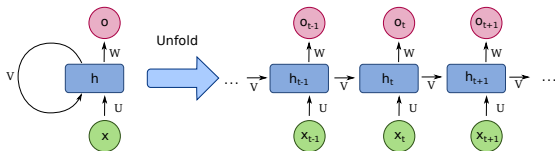
- Model context



# Recurrent neural networks (RNN)

## Keys idea

- Model context



## Problems

- Hard to train
- Exploding/vanishing gradient

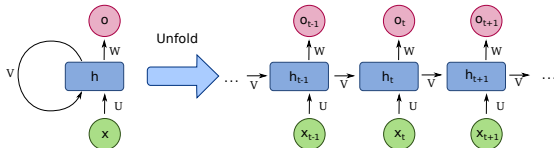
Image source : wikimedia



# Recurrent neural networks (RNN)

## Keys idea

- Model context



## Solutions

- LSTM, GRU...

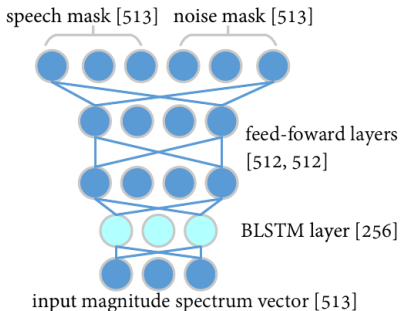
Image source : wikimedia

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# DNN-base mask estimation for multichannel filtering

Use LSTM to estimate speech/noise masks [Heymann et al.].

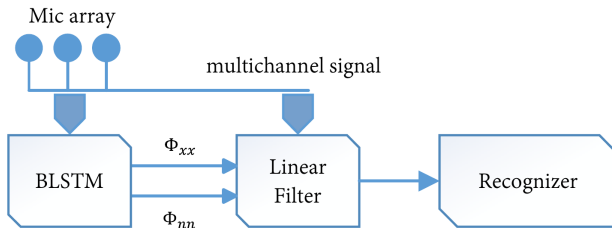


• J. Heymann, L. Drude, R. Haeb-Umbach. *Neural network based spectral mask estimation for acoustic beamforming*. Proc ICASSP 2016

# DNN-base mask estimation for MWF

[Z. Wang]

Use the masks to estimate the correlation matrices and MWF filters.



• Z. Wang, E. Vincent, R. Serizel, Y. Yan. *Rank-1 Constrained Multichannel Wiener Filter for Speech Recognition in Noisy Environments*. Computer Speech and Language

## Exemple performance


Evaluation in terms of word error rate (WER).

Noisy		WER baseline
Single-channel DNN		no WER reduc.
Delay-and-sum		21% rel. WER reduc.
DNN post-filter		20% rel. WER reduc.
Multichannel DNN		39% rel. WER reduc.

Greatly outperforms multichannel NMF (25% rel. WER reduc.)  
and DNN used to directly predict multichannel filters.

CHiME-3 : speech recorded in a bus/café. Single DNN iteration, no post-processing.

• A. A. Nugraha, A. Liutkus, E. Vincent. *Multichannel audio source separation with deep neural networks*.  
IEEE/ACM TASLP, 24 (9), pp. 1652 - 1664, 2016.



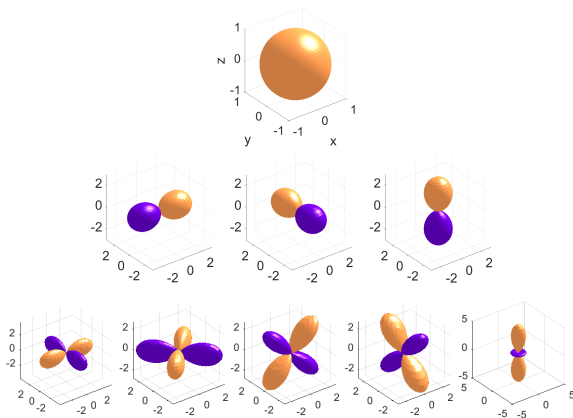
# What input should we give to the network ?

(Part of Phd work from L. Perotin)

[With E. Vincent and A. Guérin]

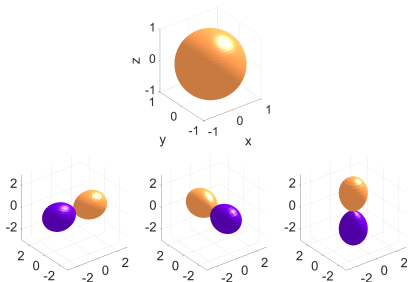
# Multichannel speech enhancement for HOA

Represent the sound field in a basis of spherical harmonics



# Multichannel speech enhancement for HOA

Use only the 4 channels from the first 2 orders

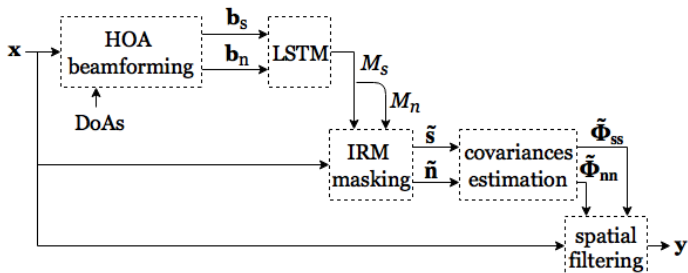


• L. Perotin, R. Serizel, E. Vincent, A. Guérin. *Multichannel speech separation with recurrent neural networks from high-order ambisonics recordings*. In proc. of ICASSP, 2018.



# Multichannel speech enhancement for HOA [L. Perotin]

- HOA beamformer
- LSTM to estimate speech/noise masks
- GEVD-MWF filter



• L. Perotin, R. Serizel, E. Vincent, A. Guérin. *Multichannel speech separation with recurrent neural networks from high-order ambisonics recordings*. In proc. of ICASSP, 2018.


# Results

## Setup

- Tested on a subset of ESTER
- 20 sentences (4043 words)
- Acoustic conditions :  $TR_{60}=350\text{ms}$ , room-mic = 1.65m

## Results

Interference	noise	speaker		
		25°	45°	90°
Reverberant source	9.80	10.80	10.82	10.76
Mixture	68.25	91.96	88.56	89.00
Simple beamformer	40.80	75.42	39.06	20.54
GEVD (w/o noise est.)	21.69	78.43	18.55	12.02
GEVD (w noise est.)	21.72	23.1	16.05	12.47

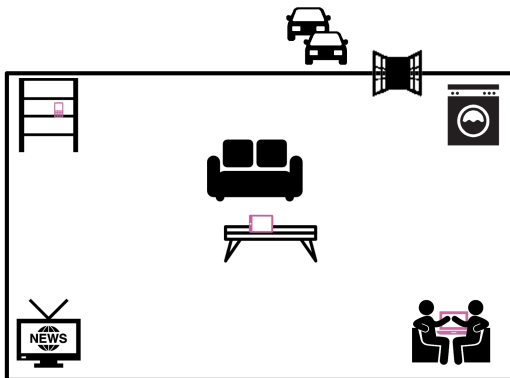


# How can we deal with ad-hoc microphone arrays ? (Part of Phd work from N. Furnon) [With I. Illina and S. Essid]

# Heterogeneous unconstrained microphone arrays

## Target :

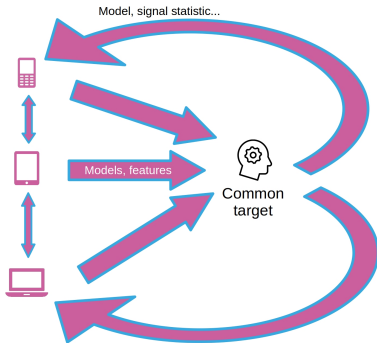
- Use the microphones already available



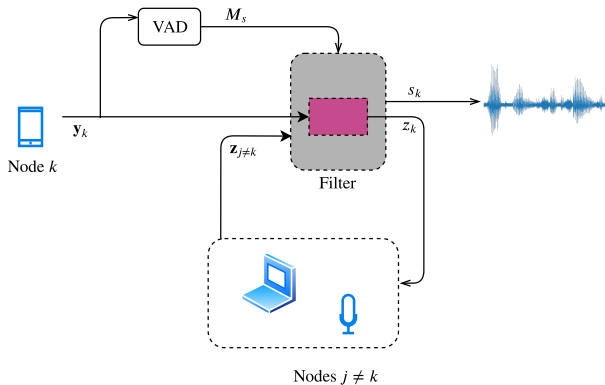
# Collaborative approach

## Targets :

- Collaboration between the nodes (common target)
- Feedback from the common target to the node level

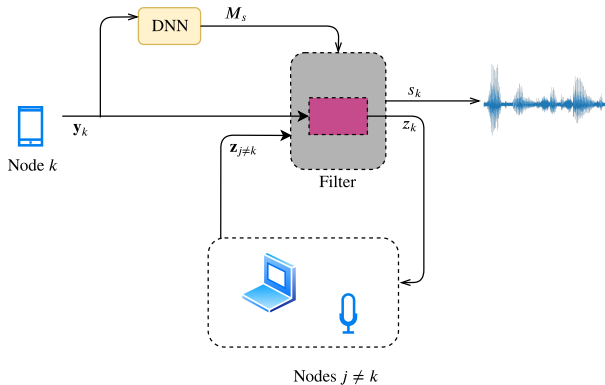


# Distributed node specific MWF



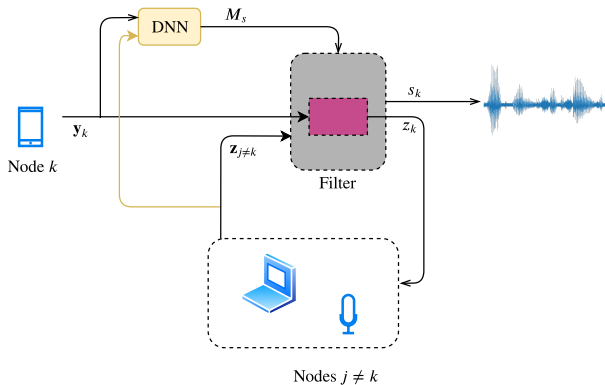
- A. Bertrand, M. Moonen. *Distributed adaptive node-specific signal estimation in fully connected sensor networks—Part I : Sequential node updating*. IEEE Transactions on Signal Processing.

# Distributed MWF with DNN [N. Furnon]



- N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays*. Submitted to ICASSP 2020.

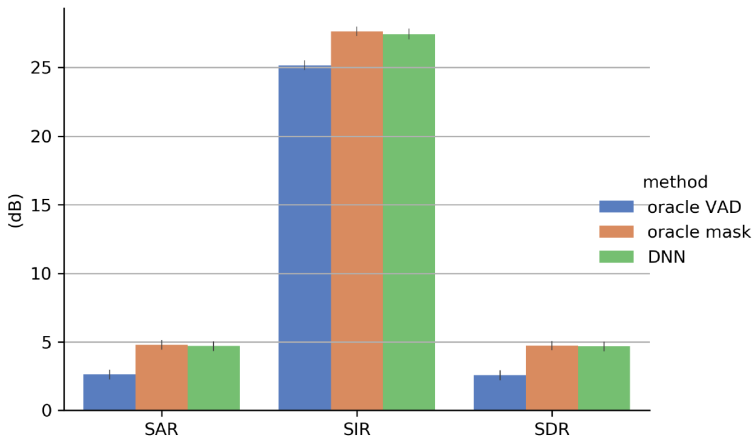
# Distributed MWF with DNN [N. Furnon]



- N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays*. Submitted to ICASSP 2020.



# Distributed MWF with DNN (Results)



• N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays*. Submitted to ICASSP 2020.

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# Conclusions and perspectives

## Conclusions

- Deep learning is now the state-of-the-art in multichannel speech enhancement
- Important improvements compared to previous approaches

## Perspectives

- Unconstrained microphone array processing,
- Distributed learning,
- Application to real-world conditions,
- Extension to other related domains. . .