DeepVoice

Extracting meaningful signal representation for Speaker Recognition using deep architectures

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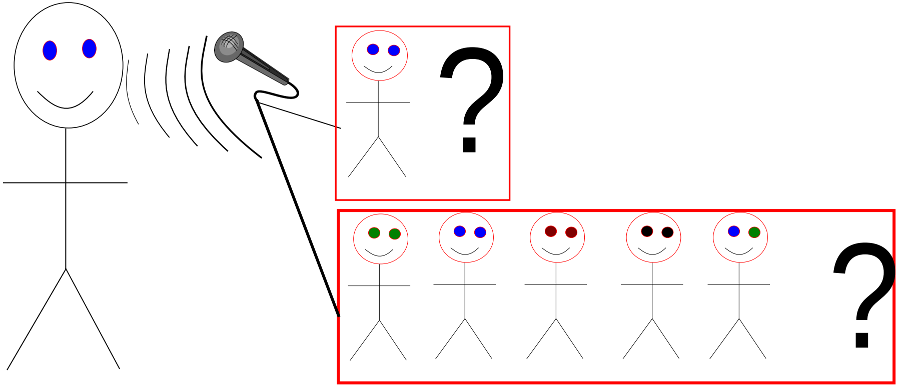
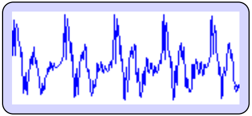
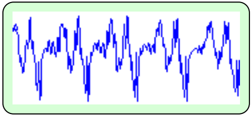
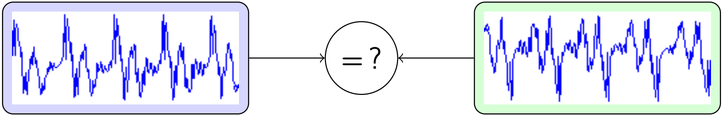
Computer science department
ENS Rennes

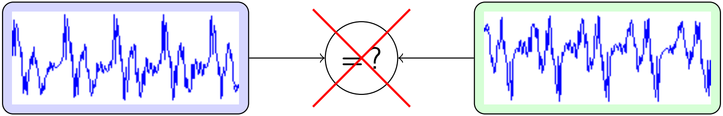
Linkmedia project
IRISA

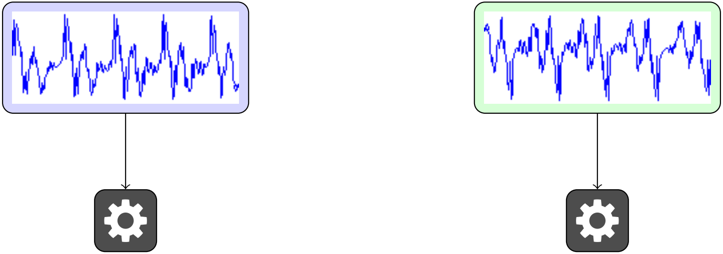


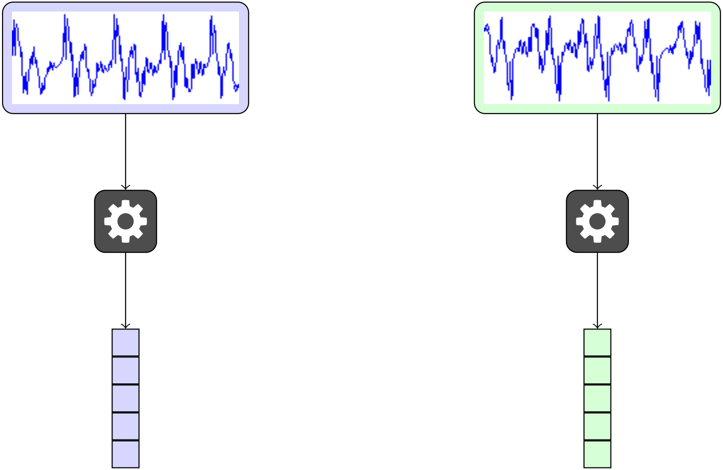


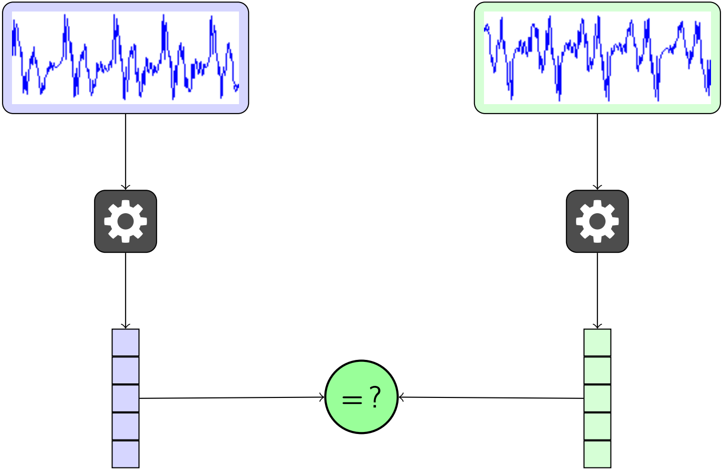


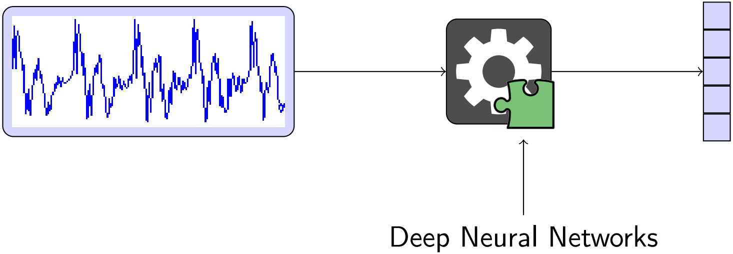








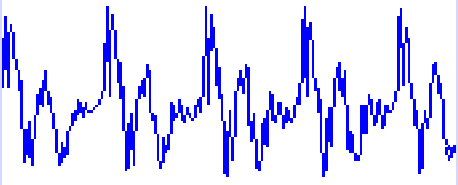



Deep Neural Networks

Outline

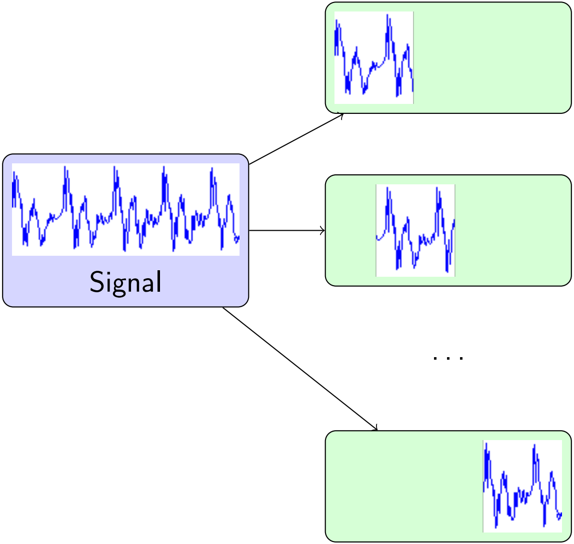
Outline

Signal processing workflow

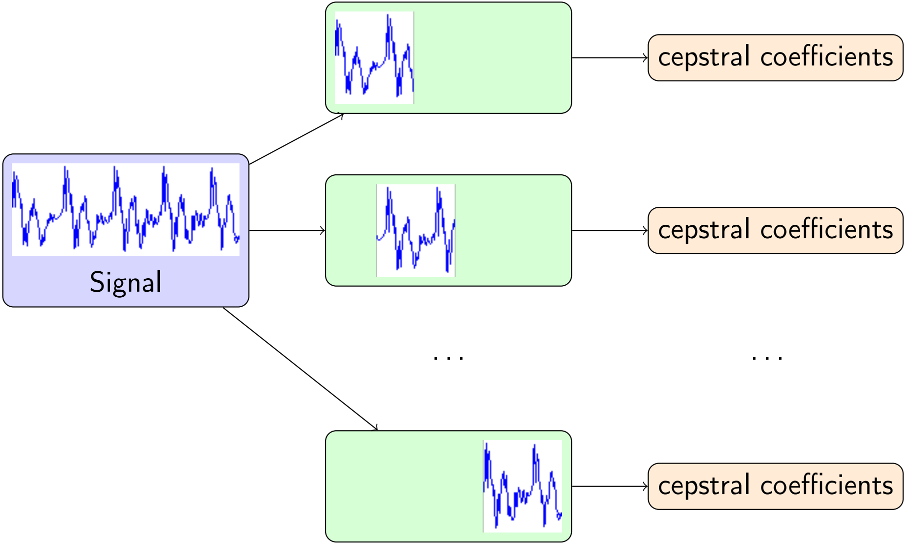


Signal

Signal processing workflow



Signal processing workflow



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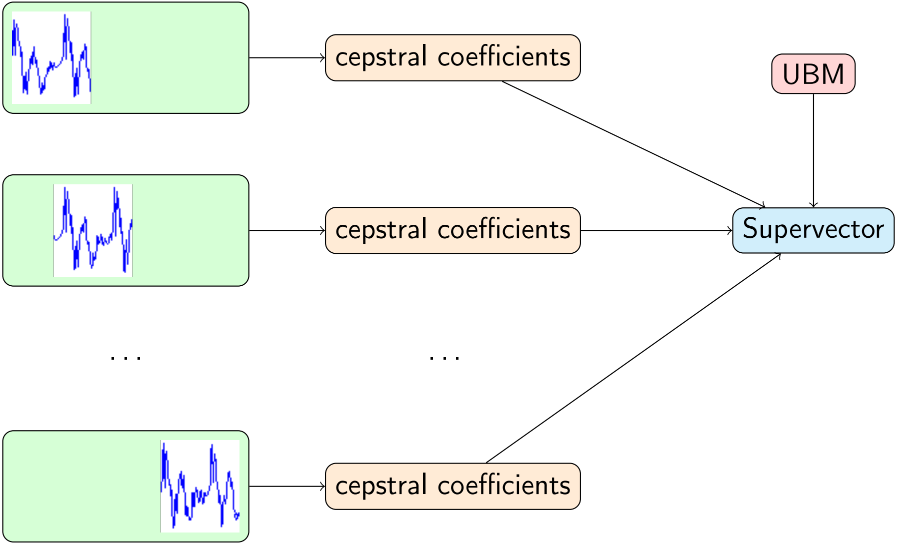
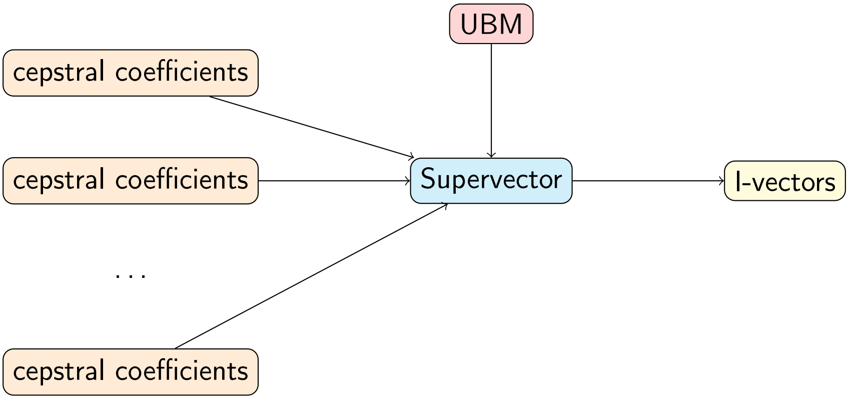


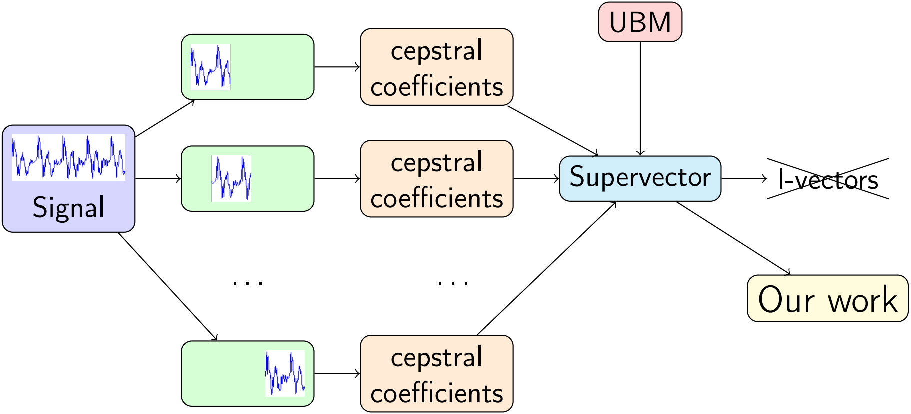
Signal processing workflow



Question

Can we do better than i-vectors ?

Signal processing workflow



Outline

Use of Deep Neural Networks (DNN)

Deep neural networks are interesting because :

- **Non-linear** feature extraction

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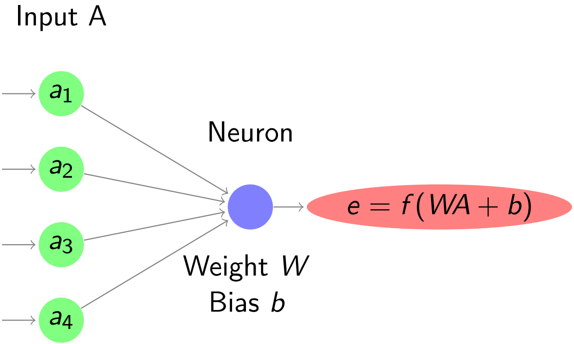
Deep neural networks are interesting because :

- **Non-linear** feature extraction
- They naturally generate several level of representation
- They bring out unsuspected features
- There is a multitude of architectures

Formal neuron



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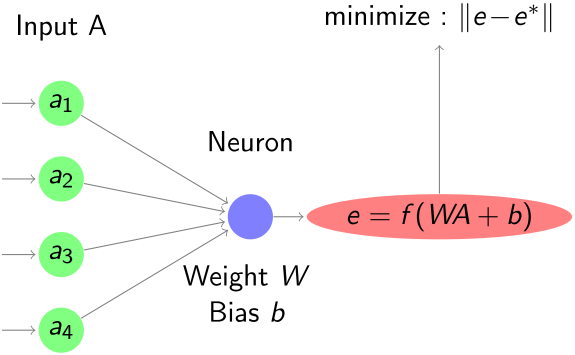

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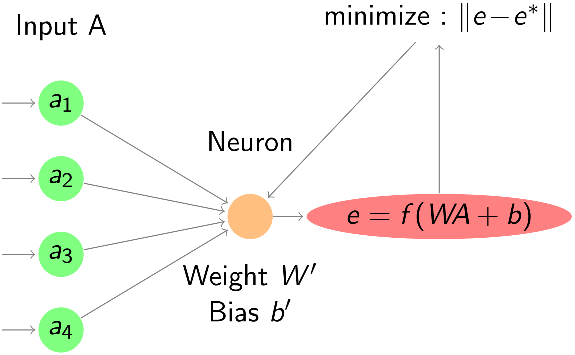

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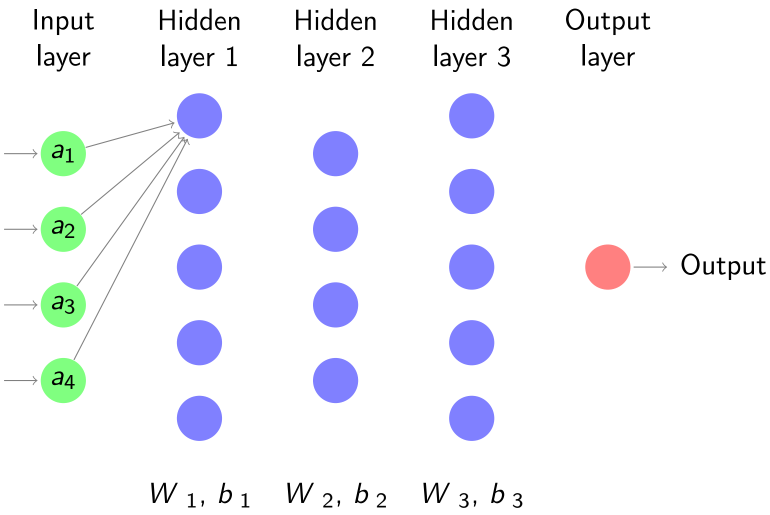
Neural network



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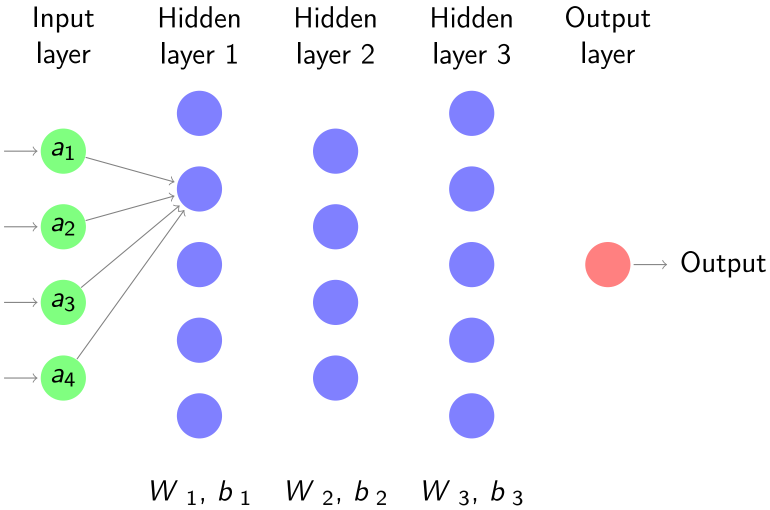

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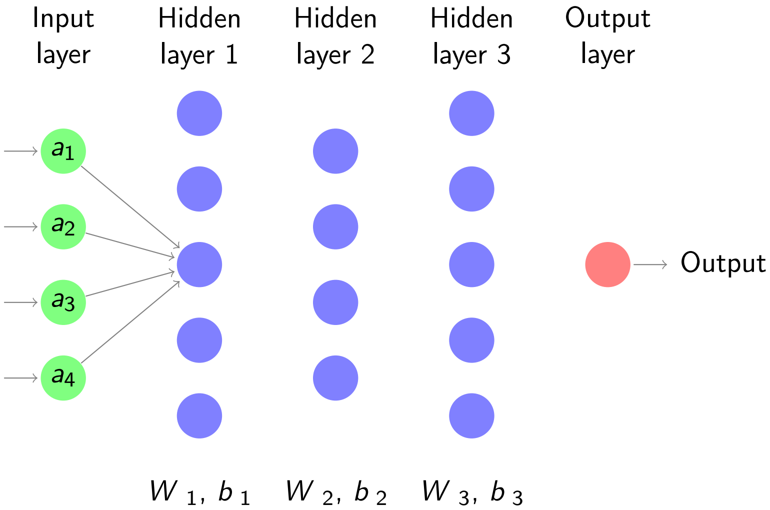

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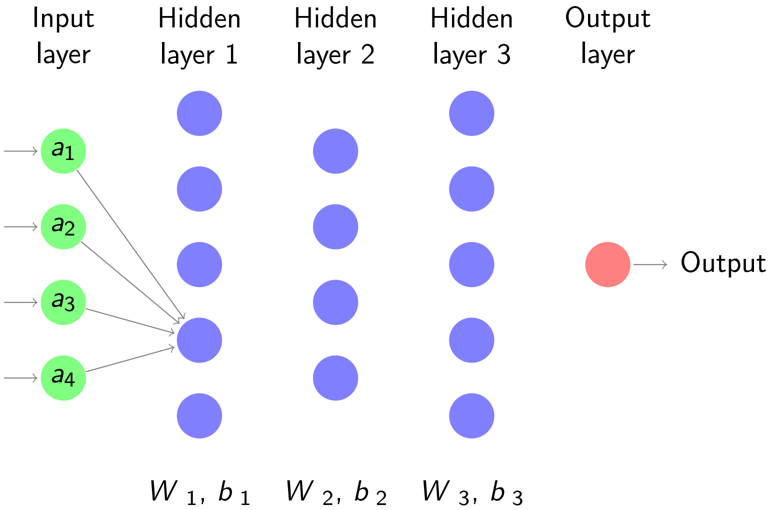

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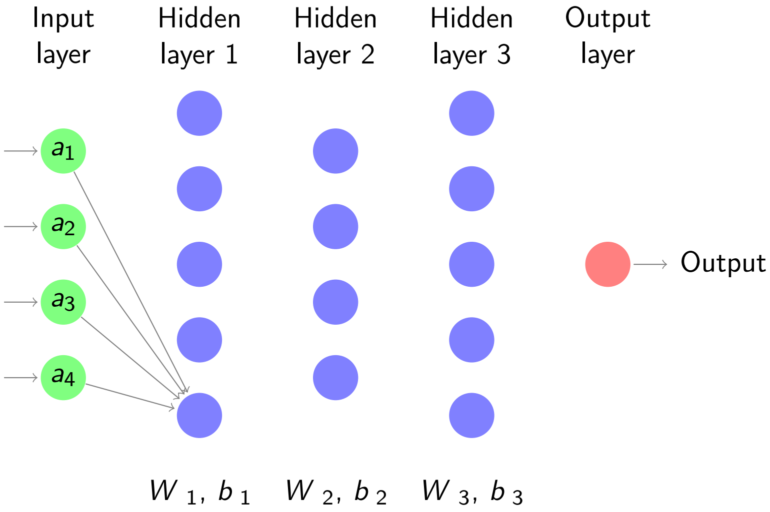

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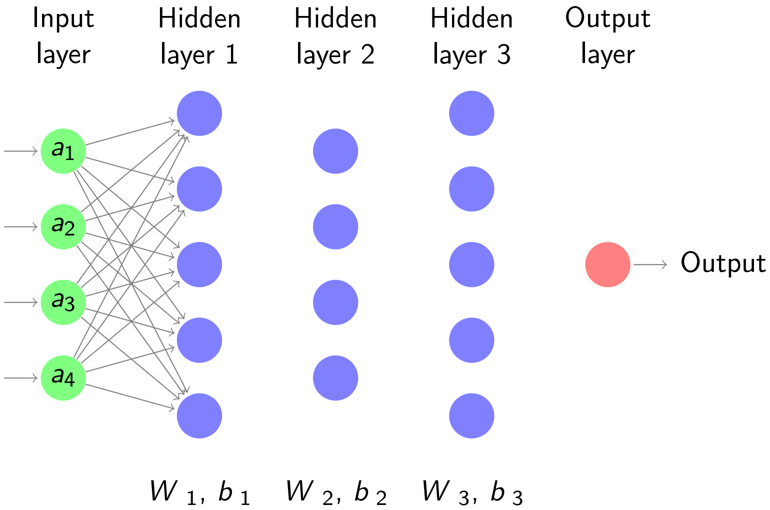

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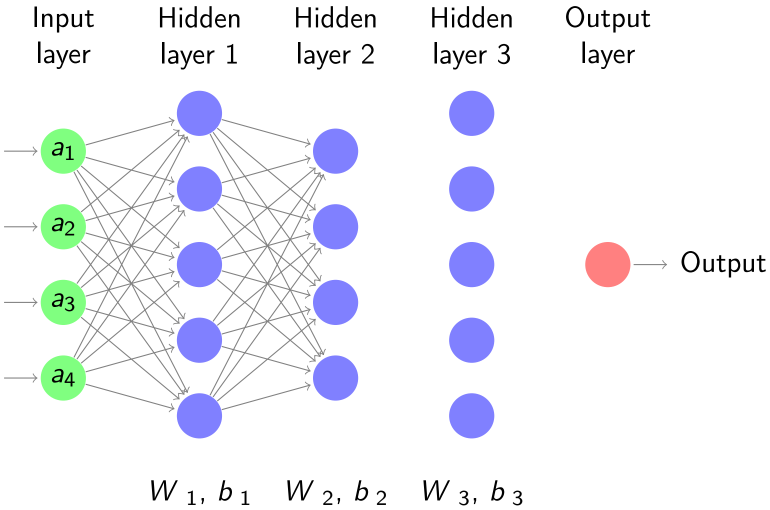

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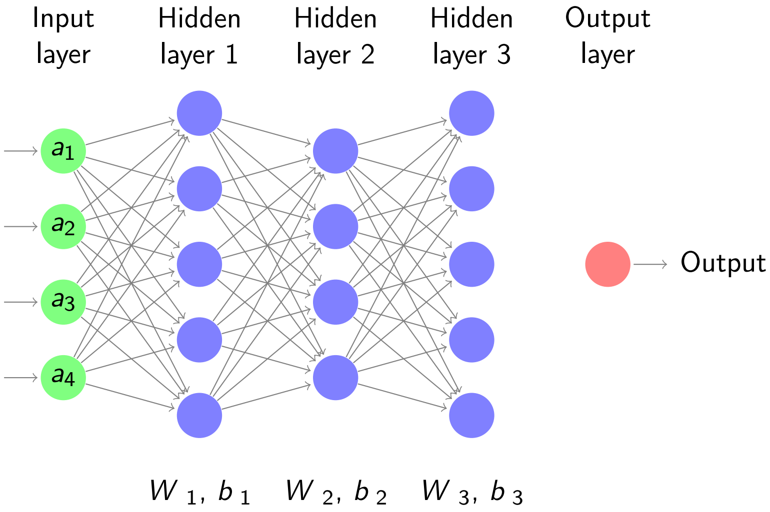

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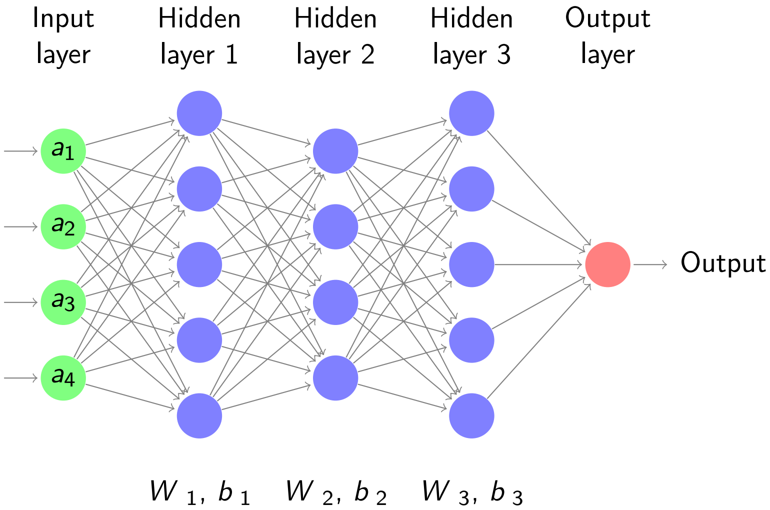

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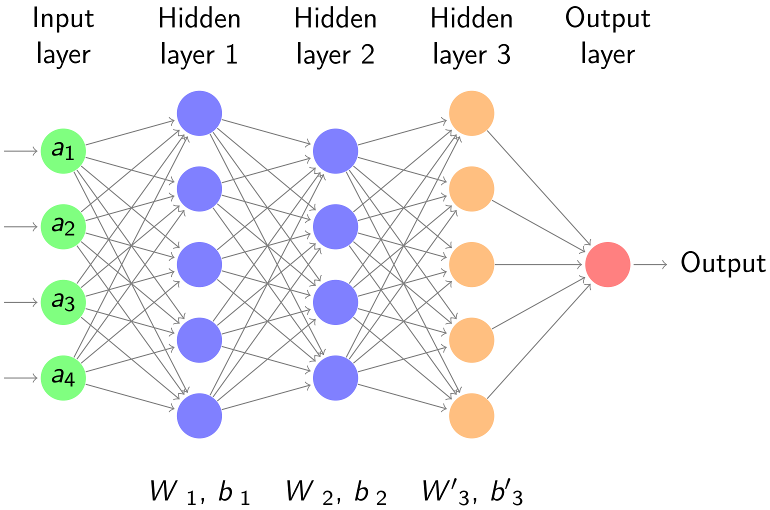

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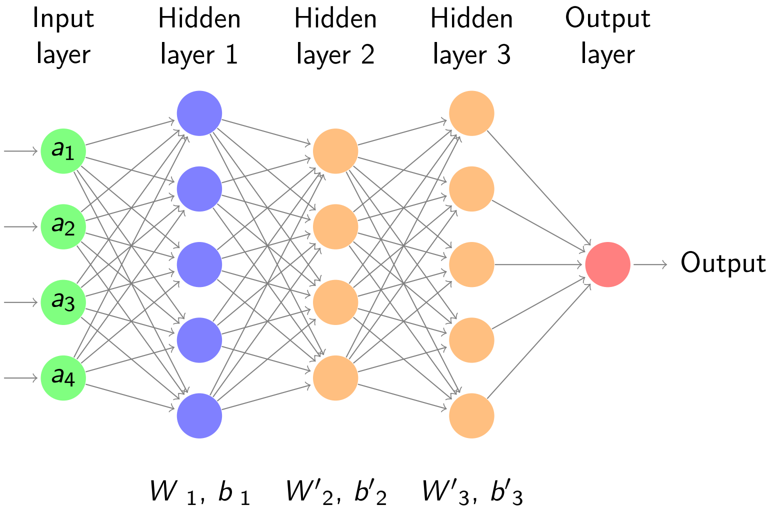

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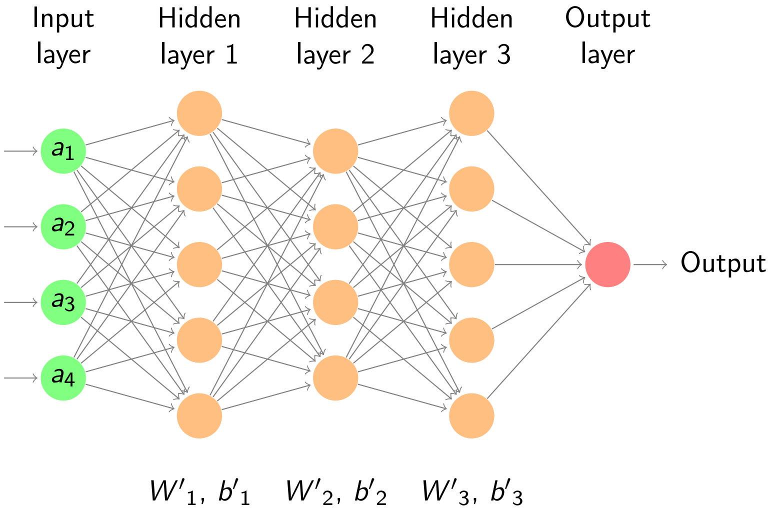
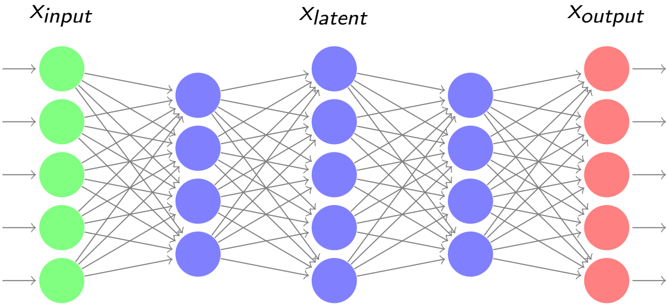
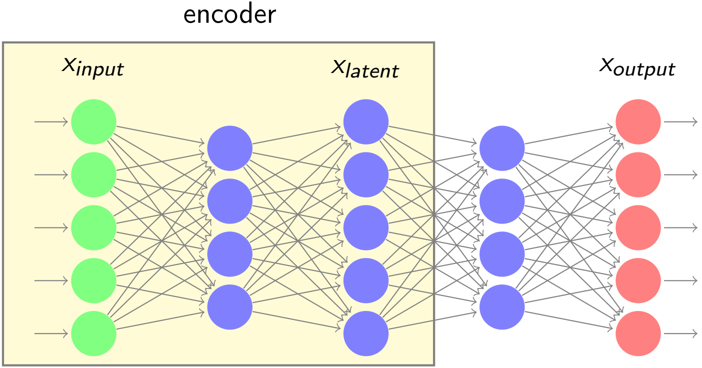


Autoencoder



G.E. Hinton and R.R. Salakhutdinov, Reducing the Dimensionality of Data with Neural Networks, Science, 28 July 2006, Vol. 313. no. 5786, pp. 504 - 507

Autoencoder



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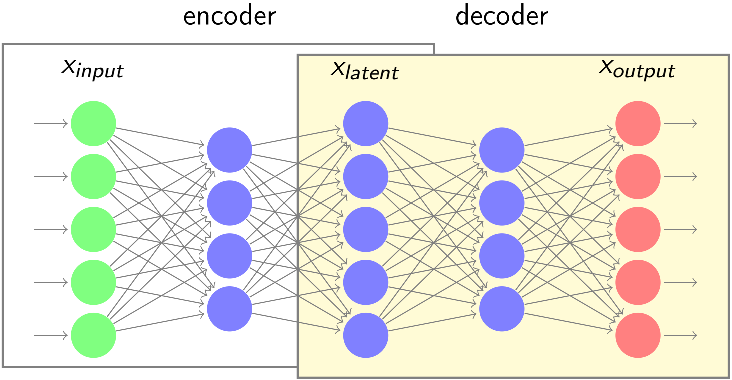

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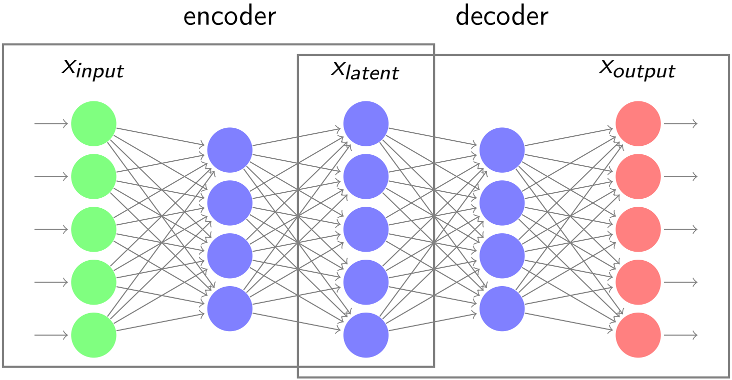

$$x_{latent} = encoder(x_{input})$$
$$x_{output} = decoder(x_{latent}) \simeq x_{input}$$

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Autoencoder

Danger : Learning the identity

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Autoencoder

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Several solutions :

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Compressing [1] :
$size(x_{latent}) < size(x_{input})$

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Several solutions :

Compressing [1] :
$size(x_{latent}) < size(x_{input})$

Adding noise [2] :
$x_{input} = objective + noise$

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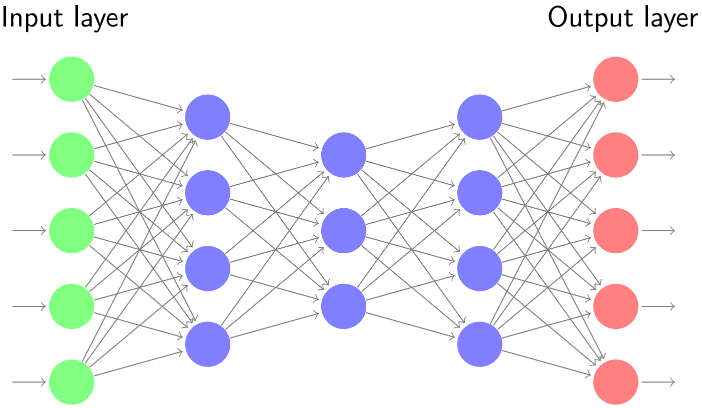
New representation



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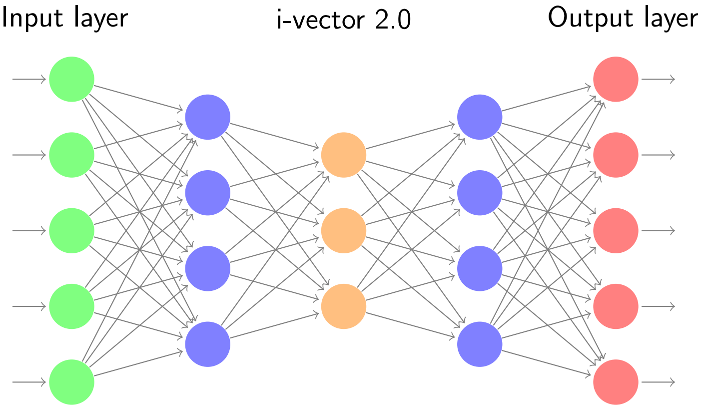

Outline

Filtering out non-speaker noise

- Filter out non-speaker dependant features

$$M = m + Tw$$

Filtering out non-speaker noise

- Filter out non-speaker dependant features (noise)
- Need to denoise the signal

$$M = noise + s_{speaker}$$

Filtering out non-speaker noise

- Filter out non-speaker dependant features (noise)
- Need to denoise the signal
- Same speaker, different signals
- Same signal, different non-speaker dependant noise

$$M_1 = noise_1 + s_{speaker}$$
$$M_2 = noise_2 + s_{speaker}$$
$$s_{speaker} = encode(M)$$

Processed data

- **Raw data :** 15311 numeric sound files from BFMTV with labeled speakers
- **Pre-processed data :** 3 678 470 pairs (v_1, v_2) of supervectors spoken by the same person
- **Input :** Supervector v_1 of length 2304
- **Output :** Supervector v_2 of length 2304

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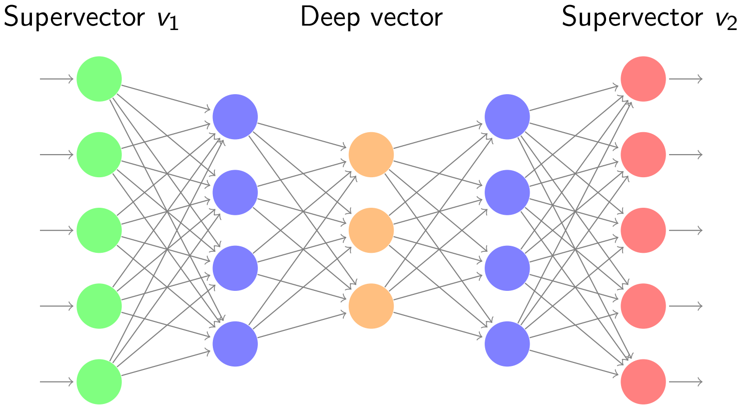
$$\begin{bmatrix} v_1^{0,0} \\ v_1^{0,1} \\ \cdots \\ v_1^{0,255} \\ v_1^{1,0} \\ .. \\ v_1^{N,255} \end{bmatrix} \begin{bmatrix} v_2^{0,0} \\ v_2^{0,1} \\ \cdots \\ v_2^{0,255} \\ v_2^{1,0} \\ .. \\ v_2^{N,255} \end{bmatrix}$$

New representation



Intermediate vector evaluation

Preliminary evaluation with cosine similarity

Threshold t

$distance \leq t$
same speaker

$distance > t$
different speakers

Outline

Goals

Numeric signals represented by i-vectors for speaker recognition tasks.
We seek to offer an alternative with deep neural networks.
What does it mean to improve on i-vectors ?

- Better compression

- Better results on angular threshold

- State-of-the-art results for speaker recognition

Goals and expected issues

Numeric signals represented by i-vectors for speaker recognition tasks.
We seek to offer an alternative with deep neural networks.
What does it mean to improve on i-vectors ?

- Better compression
  - Compression size
  - Hyperparameters
  - Compromise with results
- Better results on angular threshold
  - Optimization method
  - Compromise with compression
- State-of-the-art results for speaker recognition
  - Different training sets
  - More complicated evaluation methods