DeepVoice

Extracting meaningful signal representation for Speaker Recognition using deep architectures

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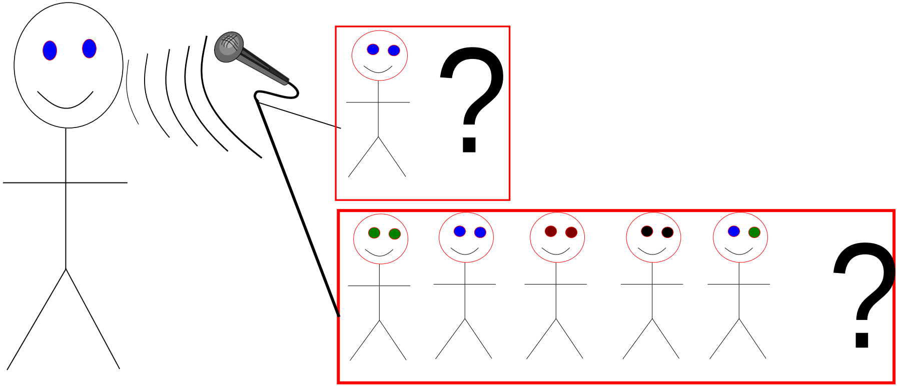
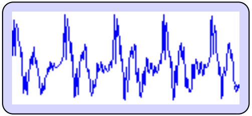
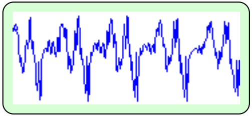
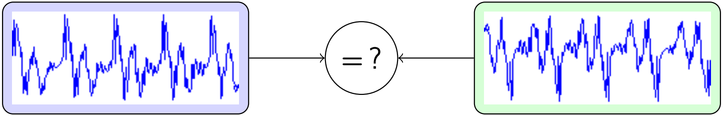
ENS Rennes

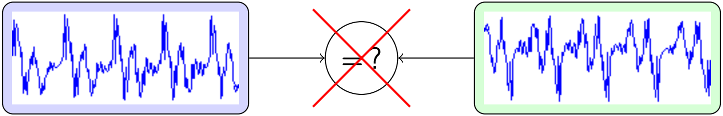
Linkmedia project
IRISA

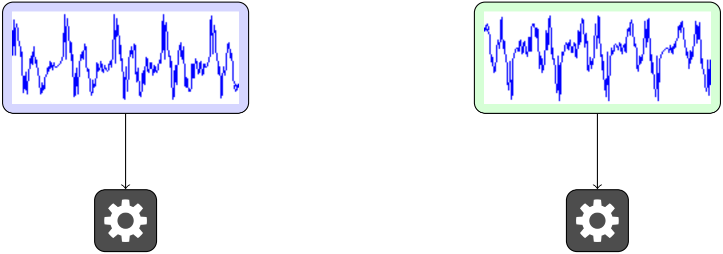


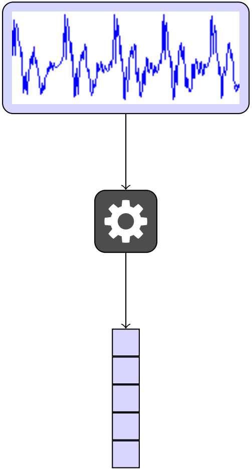


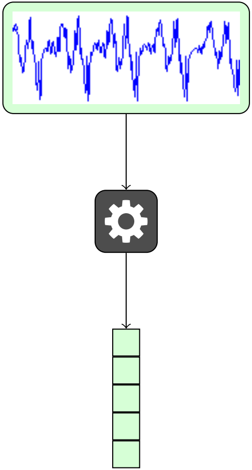


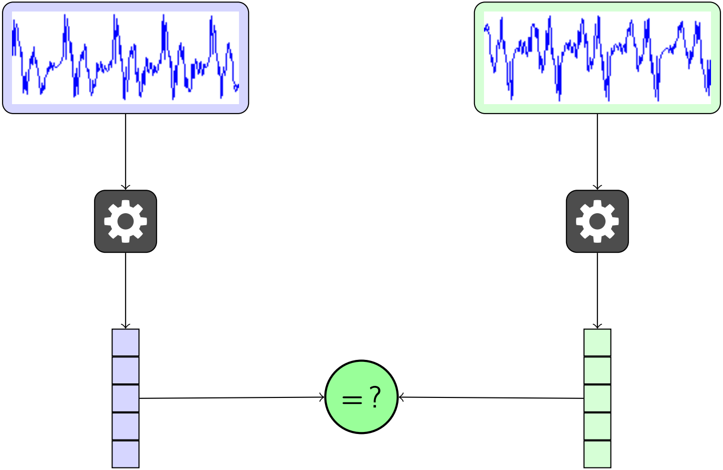


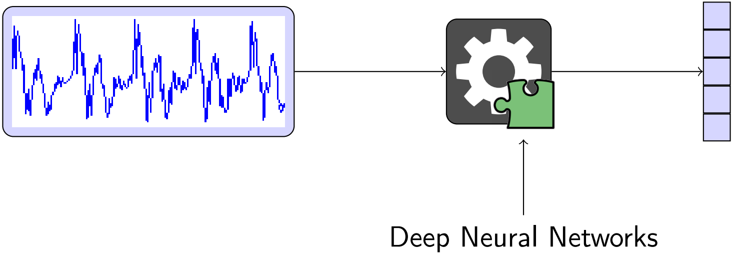








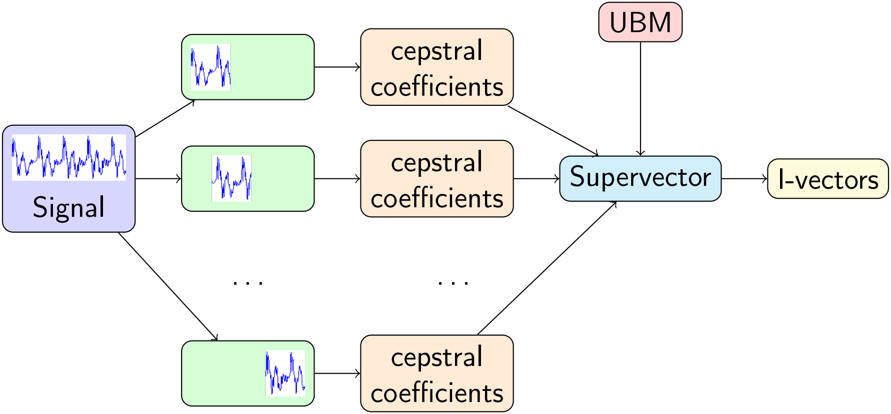



Deep Neural Networks

Outline

Outline

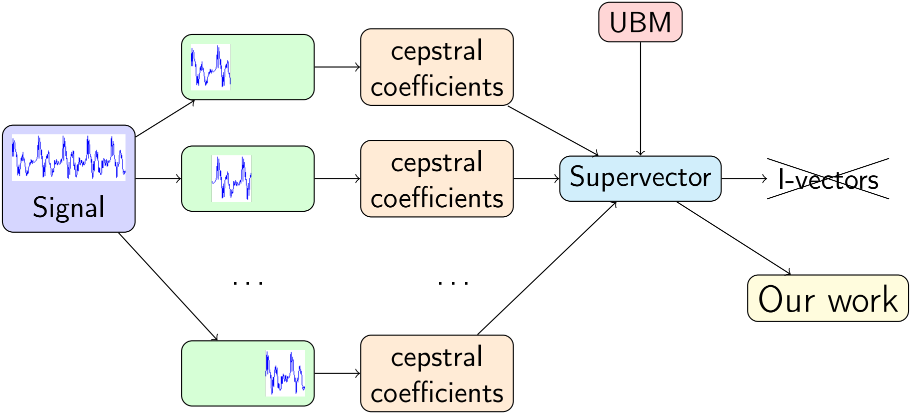
Signal processing workflow



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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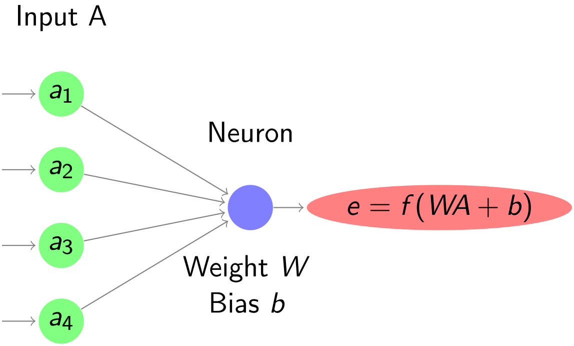
Use of Deep Neural Networks (DNN)

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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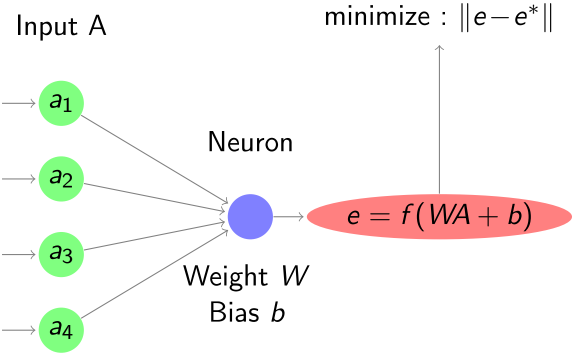
Formal neuron



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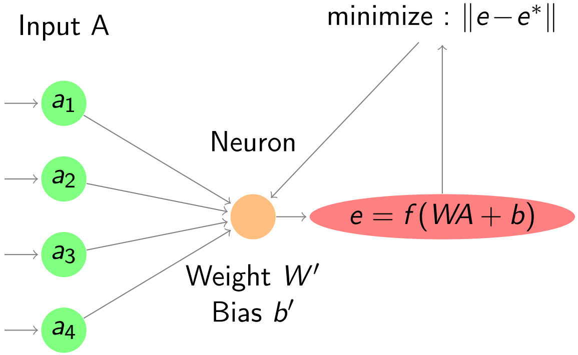

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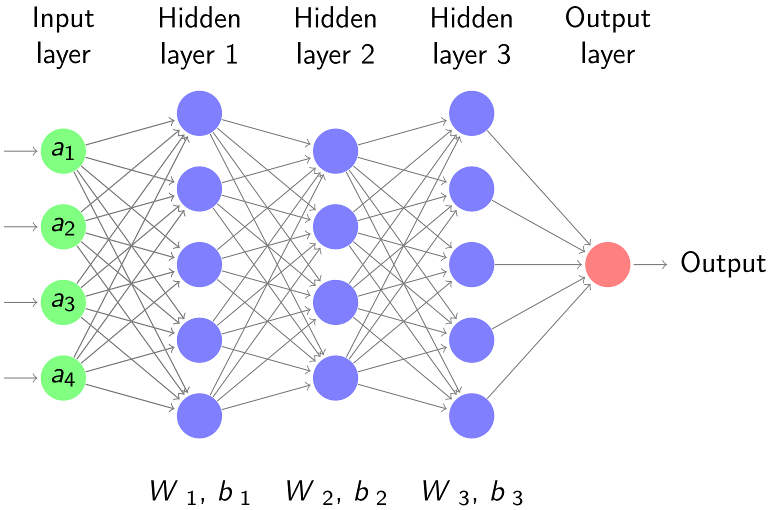
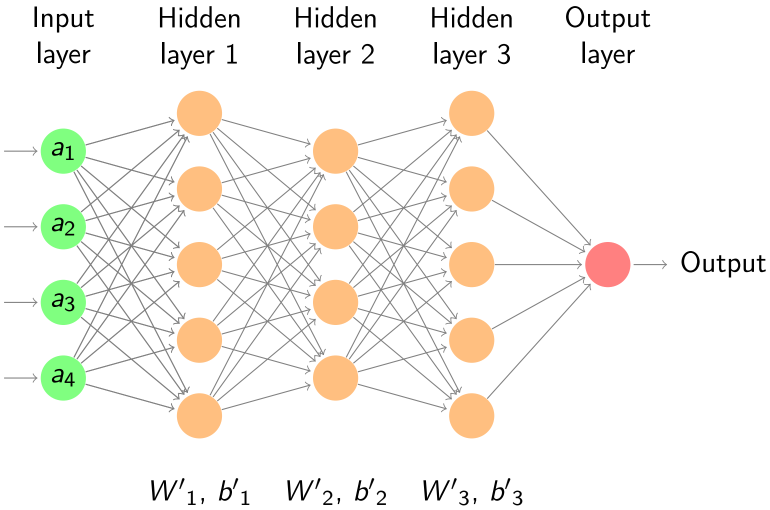
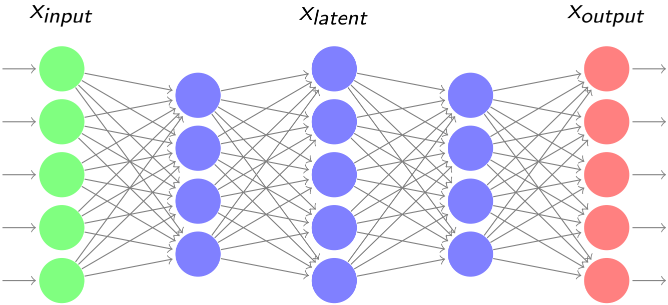
Neural network



Neural network

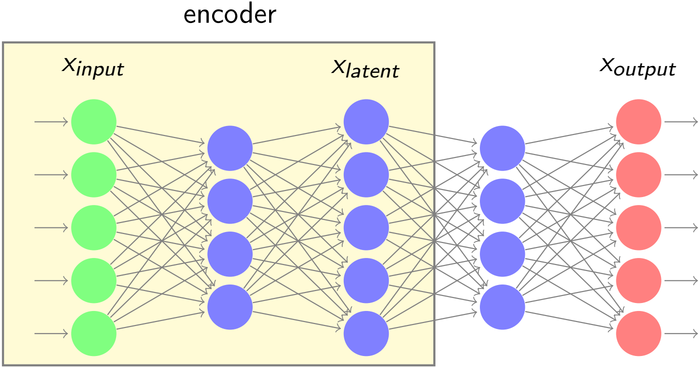


Autoencoder



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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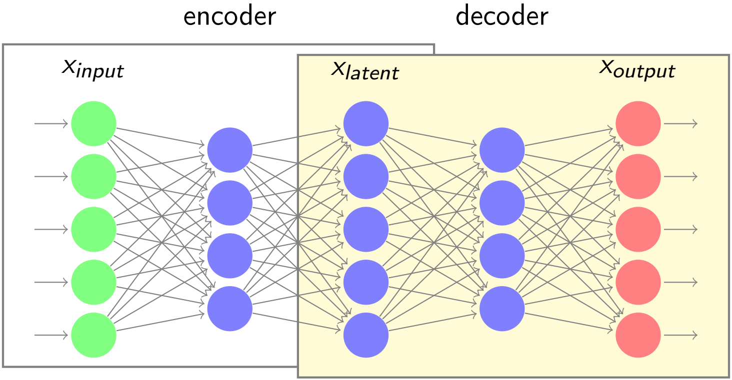

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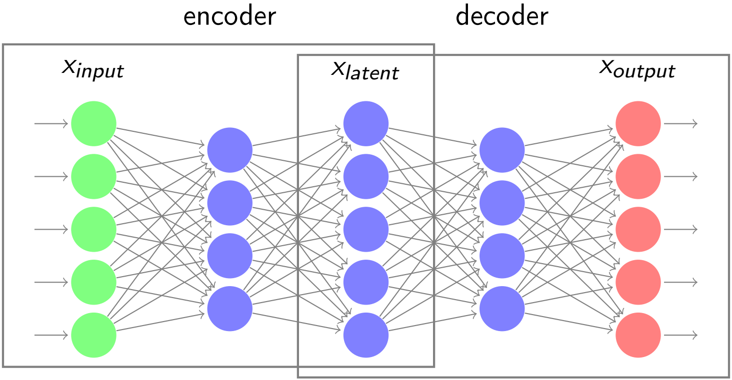

$$x_{latent} = encoder(x_{input})$$
$$x_{output} = decoder(x_{latent}) \simeq x_{input}$$

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Autoencoder

Danger : Learning the identity

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Autoencoder

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Several solutions :

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Autoencoder

Danger : Learning the identity

Several solutions :

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

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Autoencoder

Danger : Learning the identity

Several solutions :

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

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

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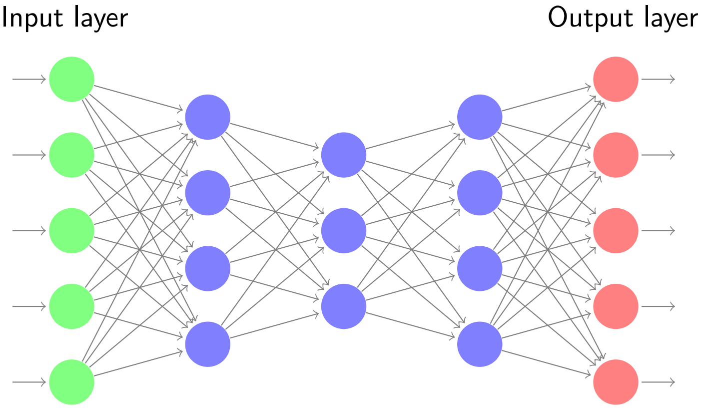
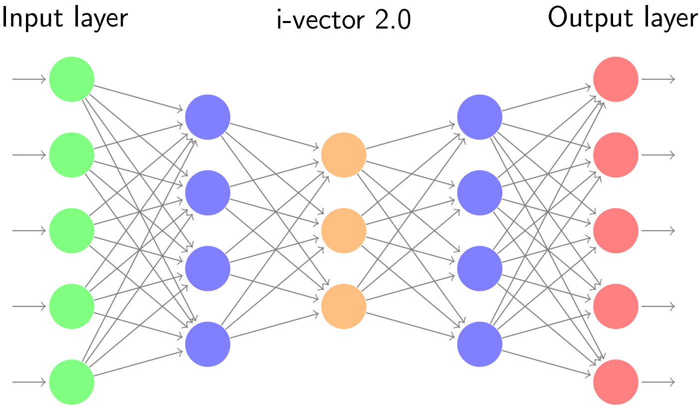
New representation



New representation



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 :** 15308 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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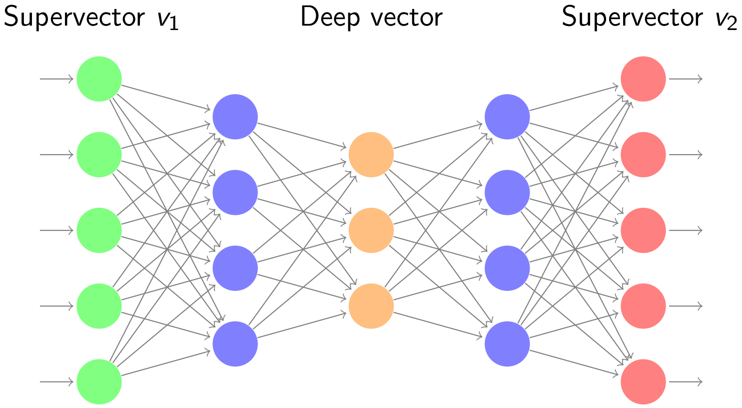
$$\begin{bmatrix} v_1^{0,0} \\ v_1^{0,1} \\ \dots \\ v_1^{0,63} \\ v_1^{1,0} \\ .. \\ v_1^{N,63} \end{bmatrix} \begin{bmatrix} v_2^{0,0} \\ v_2^{0,1} \\ \dots \\ v_2^{0,63} \\ v_2^{1,0} \\ .. \\ v_2^{N,63} \end{bmatrix}$$

New representation



Intermediate vector evaluation

Preliminary evaluation with cosine similarity

Threshold t

distance $\leq t$
same speaker

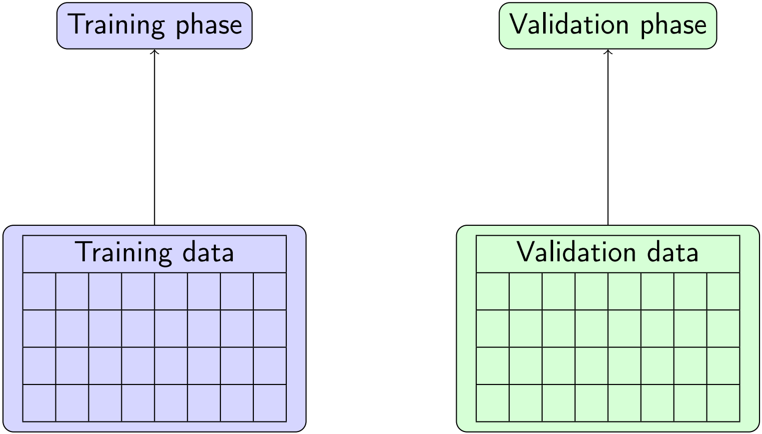
distance $> t$
different speakers

Dataset

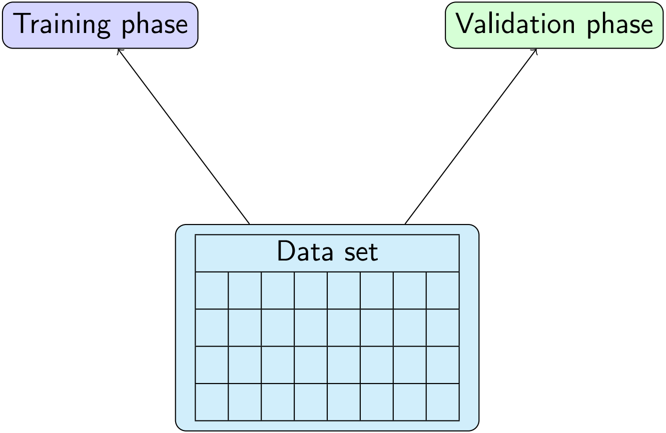
Training phase

Validation phase

Dataset

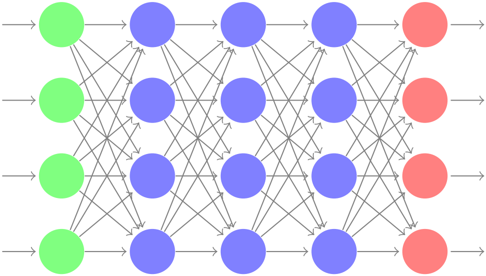

Training phase
Validation phase
Training data
Validation data

Dataset



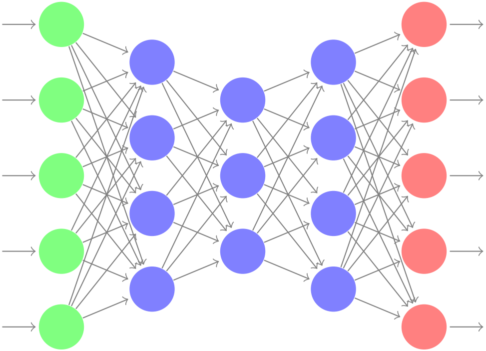
Hyper-parameters

- Number of layer



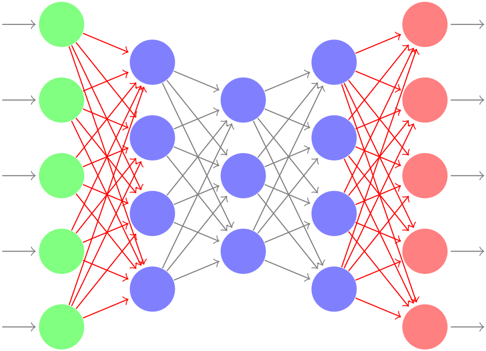
Hyper-parameters

- Number of layer
- Size of the layers



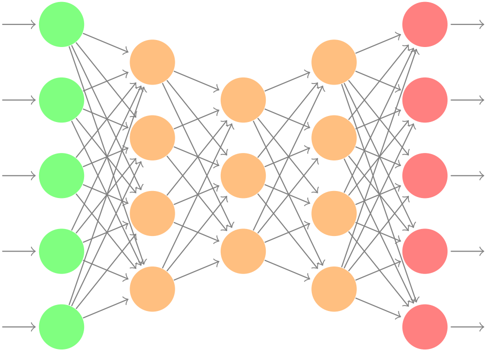
Hyper-parameters

- Number of layer
- Size of the layers
- Tied weights



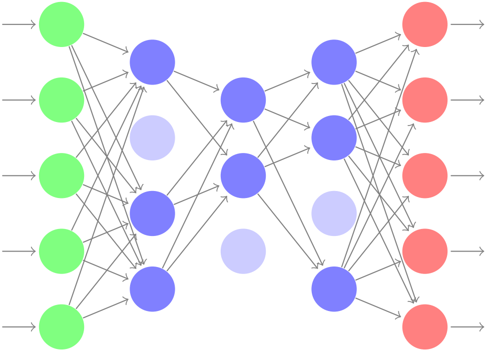
Hyper-parameters

- Number of layer
- Size of the layers
- Tied weights
- Optimizer



Hyper-parameters

- Number of layer
- Size of the layers
- Tied weights
- Optimizer
- Dropout



Outline

Repartition histograms

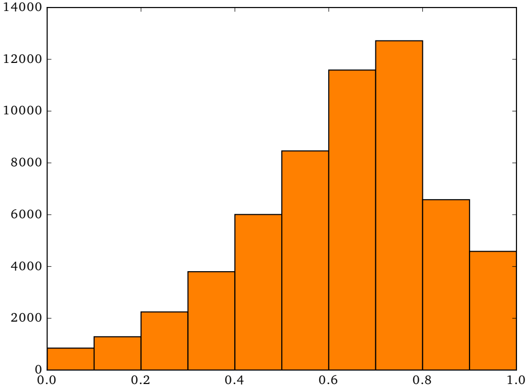


Figure – Repartition of the cosine distance between deep vectors from the same speaker

Repartition histograms

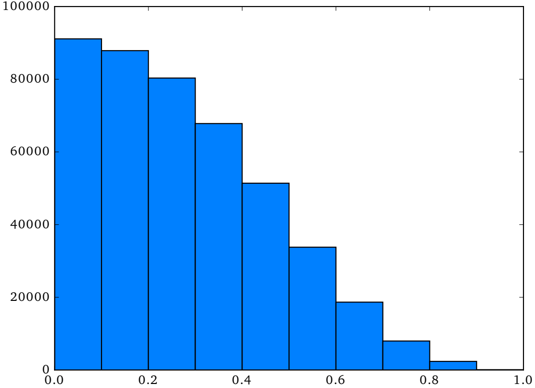


Figure – Repartition of the cosine distance between deep vectors from different speakers

Repartition histograms

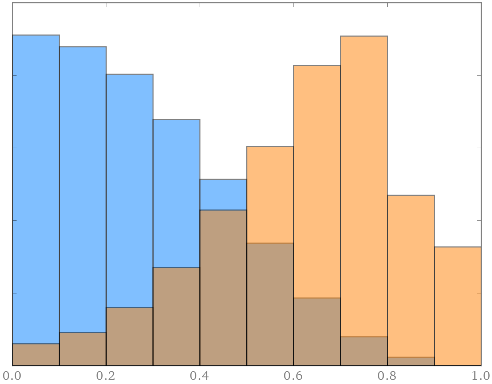


Figure – Repartition of the cosine distance between deep vectors

t-Distributed Stochastic Neighbor Embedding (t-SNE)

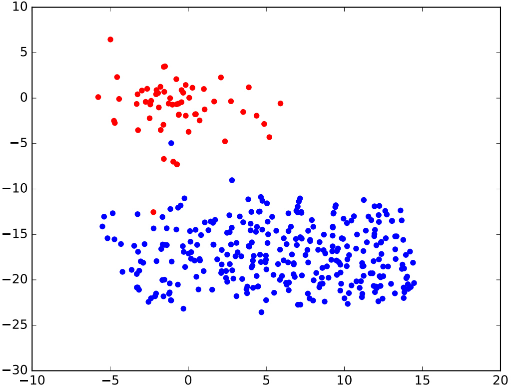
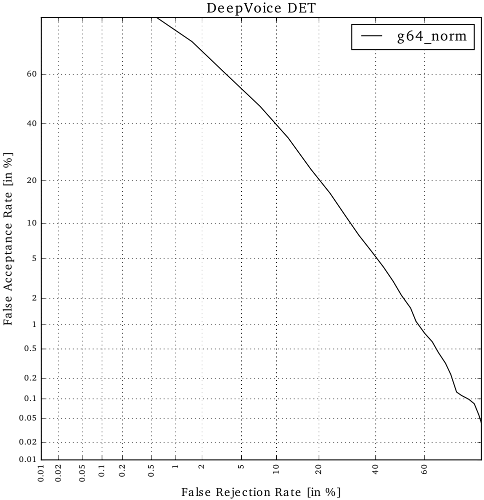


Figure – t-SNE of the deep vectors of two different speakers

Detection Error Tradeoff (DET) graph



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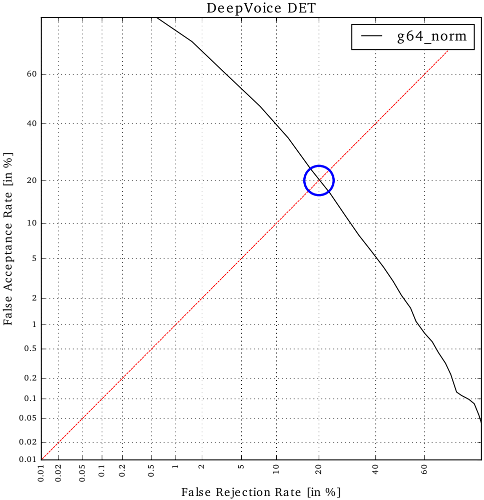
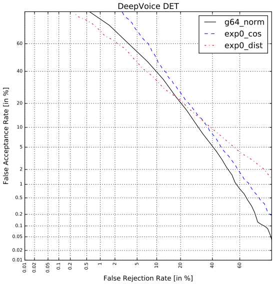


Experiment 0

Number of layers	5				
Size of layers	2304	1000	50	10000	2304
Tied weights	No				
Optimizer	Gradient Descent				
Dropout	0.90				



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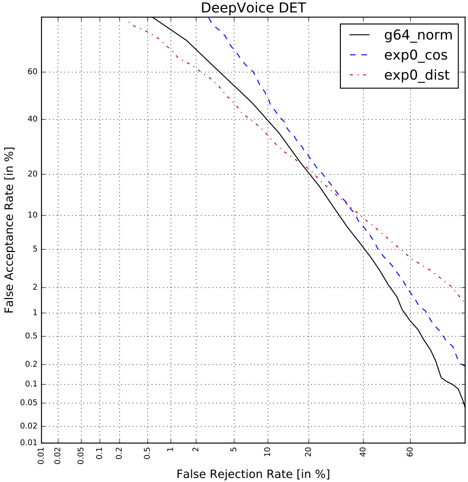
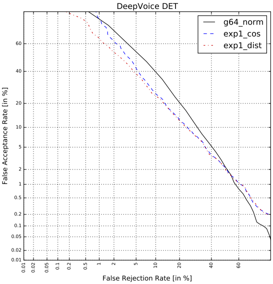


Experiment 1

Number of layers	5				
Size of layers	2304	1000	50	10000	2304
Tied weights	No				
Optimizer	Adam				
Dropout	0.90				



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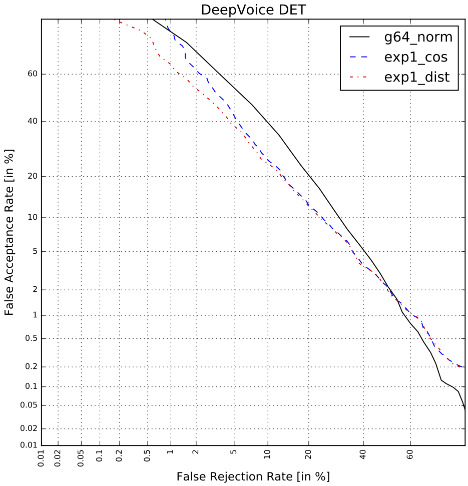
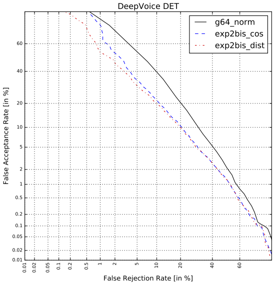


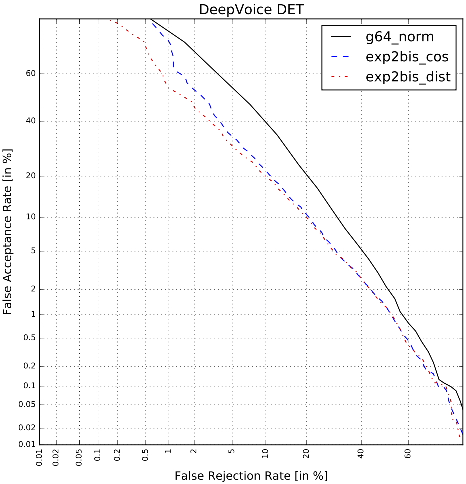
Experiment 2

Number of layers	5				
Size of layers	2304	480	100	480	2304
Tied weights	No				
Optimizer	Adam				
Dropout	0.90				



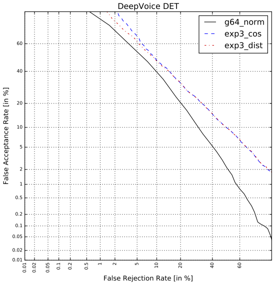
Experiment 2

Number of layers	5				
Size of layers	2304	480	100	480	2304
Tied weights	No				
Optimizer	Adam				
Dropout	0.90				



Experiment 3

Number of layers	7						
Size of layers	2304	720	225	70	225	720	2304
Tied weights	No						
Optimizer	Adam						
Dropout	0.90						



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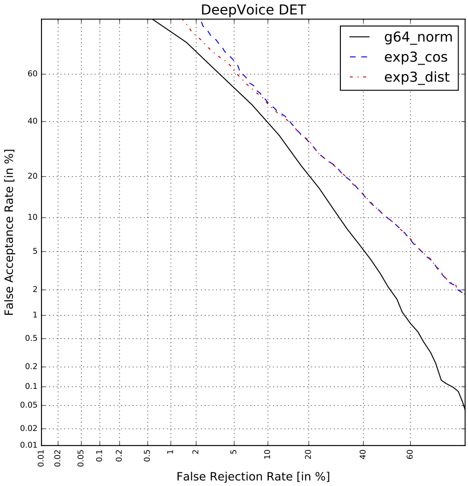
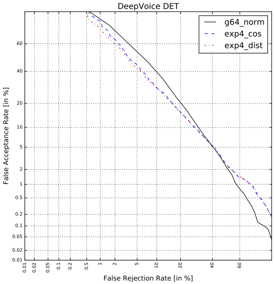
Number of layers	7						
Size of layers	2304	720	225	70	225	720	2304
Tied weights	No						
Optimizer	Adam						
Dropout	0.90						



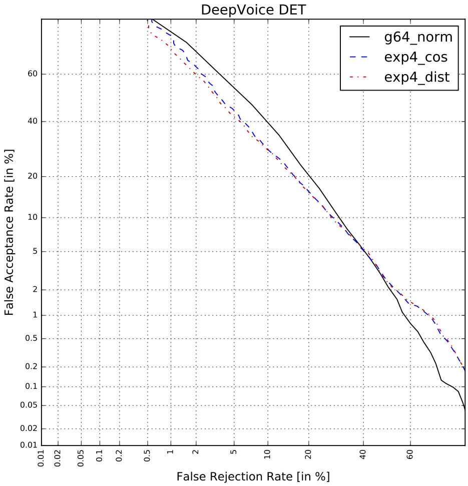
Experiment 4

Number of layers	7						
Size of layers	2304	720	225	70	225	720	2304
Tied weights	Yes						
Optimizer	Adam						
Dropout	0.90						



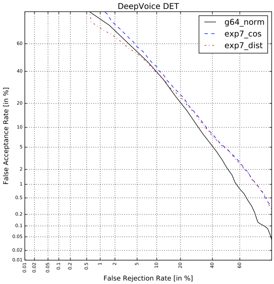
Experiment 4

Number of layers	7						
Size of layers	2304	720	225	70	225	720	2304
Tied weights	Yes						
Optimizer	Adam						
Dropout	0.90						



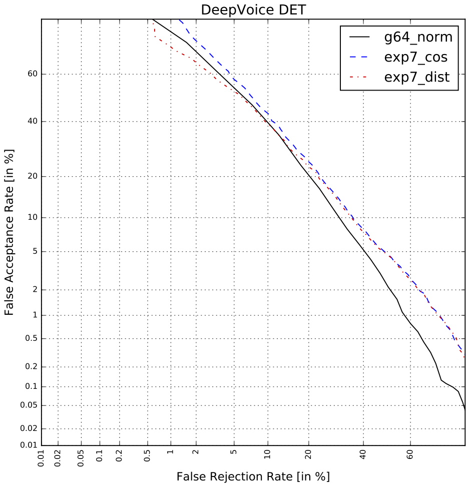
Experiment 7

Number of layers	5				
Size of layers	2304	500	80	500	2304
Tied weights	No				
Optimizer	Adam				
Dropout	0.80				



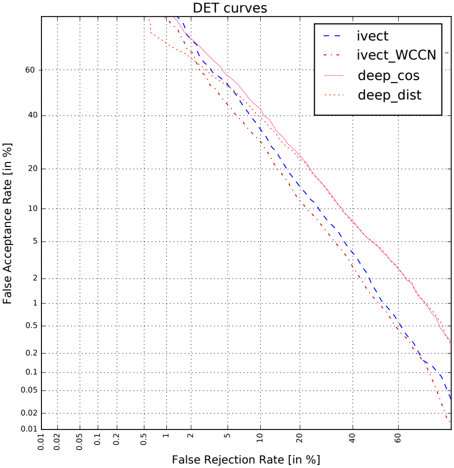
Experiment 7

Number of layers	5				
Size of layers	2304	500	80	500	2304
Tied weights	No				
Optimizer	Adam				
Dropout	0.80				



Outline

Deep-vectors vs. i-vectors



Further work

- Run additional experiments
- Adjust the hyper-parameters
- Run more experiments with disjoint training set and evaluation set