

## Context of application



- Replacing the original voice by a new voice in a target language is referred as *dubbing*.
- Voice casting is performed by a human operator and aims to find the most suited voice for the role.

### Difficulties:

- 1 There is no formal description of voices.
- 2 Operator has too many voice-actors to cast.
- 3 The subjectivity of the choice.

## Motivations

- Approximate automatically the operator's choice to help him in future decisions.
- Learn a multilingual similarity metric beyond the simple acoustic resemblance.
- Build a character/role dedicated representational space.

## Proposed approach

We use pairwise relationship between two voices (original, dubbed) that share an abstract notion of similarity.

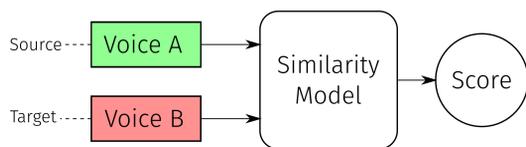


Figure 1: Voice *A* is in the source language, voice *B* in the target language. The score reflects the operator's similarity perception.

We train a binary-classifier using *Siamese Neural Networks* that learn to discriminate between *target* pairs (same character) and *non-target* pairs (different characters).

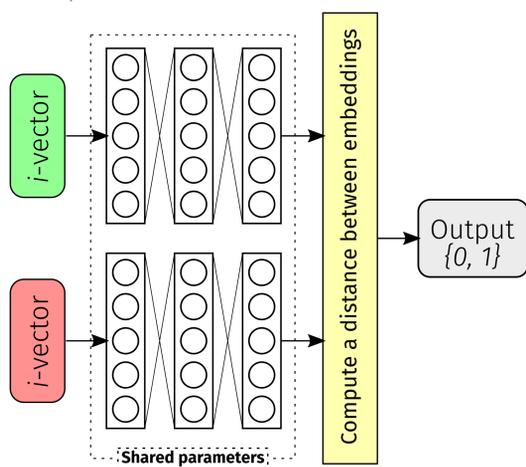


Figure 2: Siamese Neural Networks (SNN) involves two networks sharing same parameters allowing a comparison between independent inputs.

## Experimental protocol

### Corpus

- 16 characters from *Mass Effect* video-game.
- 180 voice segments per character.
- 2 different languages: *English* and *French*.

### Sequences extraction (*i*-vector):

- 19 MFCCs + energy +  $\Delta$  +  $\Delta\Delta$  with CMS and VAD.
- Language-independent *i*-vector system.
- 2048-components UBM and *T*-matrix rank 400.

Table 1: We perform a 4-fold cross-validation (jackknifing) over the 16 characters of *Mass Effect* in order to tackle the dataset limitation. Each case contains 4 distinct characters.

	Test #pairs	Training #pairs
A	64,800	B + C + D 194,400
B	64,800	A + C + D 194,400
C	64,800	A + B + D 194,400
D	64,800	A + B + C 194,400

### Evaluation:

- 1 Performance of the binary classifier (accuracy).
- 2 *Target/non-target* pairs discrimination (*t*-test).

## Results

Table 2: We compare accuracy and *t*-score of SNN with classic architectures.

	2in-conc		2in-merge		siamese-net	
	acc.	<i>t</i> score	acc.	<i>t</i> score	acc.	<i>t</i> score
A (test)	0.49	0.71	0.52	17.66	<b>0.55</b>	52.18
B (test)	0.49	5.34	0.50	4.53	<b>0.59</b>	77.99
C (test)	0.51	7.82	0.53	18.37	<b>0.62</b>	86.17
D (test)	<b>0.53</b>	17.30	0.52	14.50	0.50	1.87
A (dev)	0.94	185.72	0.93	169.93	0.72	47.90
B (dev)	0.96	211.32	0.94	190.68	0.71	52.77
C (dev)	0.93	161.16	0.93	160.16	0.70	45.18
D (dev)	0.96	227.85	0.96	212.80	0.71	44.46

SNN generalize better on 3 out of 4 test cases while standard architectures seem to memorize couple of speakers.

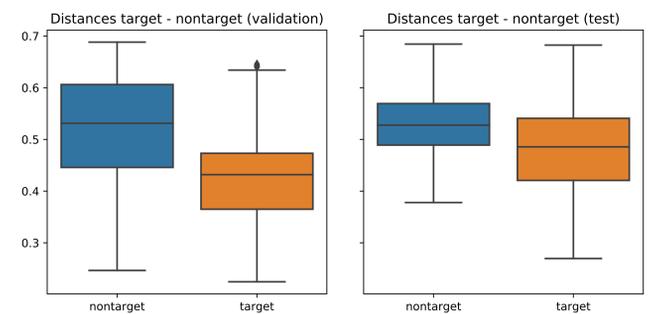


Figure 3: Target (blue) and non-target (orange) distances on case *C* for development (left) and test (right) with SNN.

## Conclusion

- Results show that we are able to discriminate *target* and *non-target* pairs on unknown voices using siamese networks.
- We built a latent representational space emphasizing the information that reflects an abstract notion of similarity.

### Limits:

- The dataset limitation.
- We do not discriminate the character himself.
- We suppose the existence of other bias.

## Perspectives

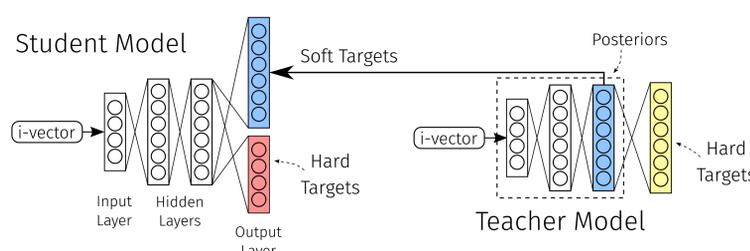


Figure 4: The teacher-student framework allows student model to learn from an intelligent teacher. We train the teacher on additional data (yellow). We use the soft-targets (blue) produced by teacher conjointly with data from *Mass Effect* (red) to train the student model.

### Knowledge distillation:

- Teacher model is a character/role classifier trained on additional data with extra labels.
- We raise the temperature in *softmax* activation layer to smooth the class probabilities distribution.
- The knowledge coming from the soft-labels help the student model to discriminate on the *Mass Effect* characters.