Odyssey 2020 The VoicePrivacy 2020 Challenge **Post evaluation analysis Voice Similarity Matrices** Ínnía -Presenter: Paul-Gauthier Noé Natalia Tomashenko 1 ¹ LIA – University of Avignon – France EURECOM Brij M.L. Srivastava² ² Inria – France Xin Wang³ ³ NII – Tokyo – Japan ⁴ Inria – France **Emmanuel Vincent**⁴ Japan Science and Technology Agency ⁵ Audio Security and Privacy Group, EURECOM – France Andreas Nautsch ⁵ G ⁶ University of Edinburgh – UK Junichi Yamagishi ^{3,6} COMPRISE ⁷ Aix-Marseille University – France Nicholas Evans ⁵ Jose Patino ⁵ Jean-François Bonastre¹ anR Commission Paul-Gauthier Noé¹ Massimiliano Todisco ⁵ Aix*Marseille Mohamed Maouche² **Benjamin O'Brien**⁷ THE UNIVERSITY of EDINBURGH Anais Chanclu¹ 4th November 2020

Speech Pseudonymisation Assessment Using Voice Similarity Matrices [Noe 2020]

Voice Similarity Matrices for the evaluation of:

- ✓ Differences in performance across speakers,
- ✓ Global De-Identification,
- ✓ Global Voice Distinctiveness Preservation.

Voice Similarity Matrix: $M = (S(i,j))_{1 \le i \le N, 1 \le j \le N}$

$$S(i,j) = sigmoid\left(\sum_{\substack{1 \le k \le n_i \\ 1 \le l \le n_j}} \frac{llr(x_k^{(i)}, x_l^{(j)})}{n_i n_j}\right)$$

where $x_q^{(p)}$ is the *q*-th segment of the *p*-th speaker, n_p is the number of segments from the *p*-th speaker and $llr(\cdot, \cdot)$ is the log likelihood-ratio score from the comparison of the two speech segments.

We build three voice similarity matrices:

- M_{OO} within the original set,
- ✓ M_{OP} between the original and pseudonymized sets,
- ✓ M_{PP} within the pseudonymised set.



Three artificial similarity matrices. The upper-left is M_{OO} , the upper-right and lower-left are M_{OP} and the lower-right is M_{PP} .

Diagonals comparison \rightarrow Insight on the global performance





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We propose two metrics based on diagonals comparison:

De-Identification:

$$DeID = 1 - \frac{D_{diag}(M_{OP})}{D_{diag}(M_{OO})}$$

Voice Distinctiveness Preservation:

$$G_{VD} = 10\log_{10}\left(\frac{D_{diag}(M_{PP})}{D_{diag}(M_{OO})}\right)$$

Where the diagonal dominance of a matrix M is defined as:

$$D_{diag}(M) = \left| \left(\sum_{1 \le i \le N} \frac{S(i,i)}{N} \right) - \left(\sum_{\substack{1 \le j \le N \\ 1 \le k \le N \\ j \ne k}} \frac{S(j,k)}{N(N-1)} \right) \right|$$



Similarity matrices: LibriSpeech-test-male



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Similarity matrices: VCTK-test-female (different)



De-Identification & Gain of voice distinctiveness: LibriSpeech

De-Identification vs Gain of voice distinctiveness



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De-Identification & Gain of voice distinctiveness: VCTK



De-Identification vs Gain of voice distinctiveness

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Voice Similarity matrices

- \checkmark Assess visually the De-Identification and Voice Distinctiveness,
- ✓ Differences of performance across speakers.

Two Metrics from the diagonals comparison

- ✓ Global De-Identification (DeID),
- ✓ Global Voice Distinctiveness Preservation (VDP),
- ✓ Most systems perform well either on DeID or on VDP but hardly on both.