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## Supplementary material to the paper **The VoicePrivacy 2020 Challenge: Results and findings**

Natalia Tomashenko, Xin Wang, Emmanuel Vincent, Jose Patino, Brij Mohan Lal Srivastava, Paul-Gauthier Noé, Andreas Nautsch, Nicholas Evans, Junichi Yamagishi, Benjamin O'Brien, et al.

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# Supplementary material to the paper The VoicePrivacy 2020 Challenge: Results and findings

Natalia Tomashenko<sup>a,\*</sup>, Xin Wang<sup>b</sup>, Emmanuel Vincent<sup>c</sup>, Jose Patino<sup>d</sup>, Brij Mohan Lal Srivastava<sup>f</sup>, Paul-Gauthier Noé<sup>a</sup>, Andreas Nautsch<sup>d</sup>, Nicholas Evans<sup>d</sup>, Junichi Yamagishi<sup>b,e</sup>, Benjamin O'Brien<sup>g</sup>, Anaïs Chanclu<sup>a</sup>, Jean-François Bonastre<sup>a</sup>, Massimiliano Todisco<sup>d</sup>, Mohamed Maouche<sup>f</sup>

<sup>a</sup>*LIA, University of Avignon, Avignon, France*  
<sup>b</sup>*National Institute of Informatics (NII), Tokyo, Japan*  
<sup>c</sup>*Université de Lorraine, CNRS, Inria, LORIA, France*  
<sup>d</sup>*Audio Security and Privacy Group, EURECOM, France*  
<sup>e</sup>*University of Edinburgh, UK*  
<sup>f</sup>*Inria, France*  
<sup>g</sup>*LPL, Aix-Marseille University, France*

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## Abstract

The VoicePrivacy 2020 Challenge focuses on developing anonymization solutions for speech technology. This report complements the summary results and analyses presented by Tomashenko et al. (2021). After quickly recalling the challenge design and the submitted anonymization systems, we provide more detailed results and analyses. First, we present objective evaluation results for the primary challenge metrics and for alternative metrics and attack models, and we compare them with each other. Second, we present subjective evaluation results for speaker verifiability, speech naturalness, and speech intelligibility. Finally, we compare these objective and subjective evaluation results with each other.

*Keywords:* privacy, anonymization, speech synthesis, voice conversion, speaker verification, automatic speech recognition, attack model, metrics, utility

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\*Corresponding author

Email address: [natalia.tomashenko@univ-avignon.fr](mailto:natalia.tomashenko@univ-avignon.fr) (Natalia Tomashenko)

## 1. Challenge design (summary)

Privacy preservation is formulated as a game between *users* who publish some data and *attackers* who access this data or data derived from it and wish to infer information about the users (Tomashenko et al., 2020b; Qian et al., 2018; Srivastava et al., 2020b).

Users (speakers) want to hide their identity while allowing all other downstream goals to be achieved. Attackers want to identify the speakers from one or more utterances.

The task of challenge participants is to develop an anonymization system. It should: (a) output a speech waveform, (b) hide speaker identity, (c) leave other speech characteristics unchanged, (d) ensure that all trial utterances from a given speaker are uttered by the same pseudo-speaker, while trial utterances from different speakers are uttered by different pseudo-speakers.

We consider objective and subjective privacy metrics to assess speaker re-identification and linkability. We also propose objective and subjective utility metrics in order to assess the fulfillment of the user goals. Specifically, we consider ASR performance using a model trained on clean and anonymized data, as well as subjective speech intelligibility and naturalness.

For objective evaluation of anonymization performance, two systems were trained to assess the following characteristics: speaker verifiability and ability of the anonymization system to preserve linguistic information in the anonymized speech. The first system, denoted  $ASV_{eval}$ , is an automatic speaker verification (ASV) system. The second system, denoted  $ASR_{eval}$ , is an automatic speech recognition (ASR) system. These two systems were used in the VoicePrivacy official challenge setup (Tomashenko et al., 2020b,a). In addition, we trained ASV and ASR systems on anonymized speech data:  $ASV_{eval}^{anon}$  and  $ASR_{eval}^{anon}$ .

The **objective evaluation** metrics for privacy and utility include:

1. Equal error rate (EER);
2. Log-likelihood-ratio cost function ( $C_{llr}$  and  $C_{llr}^{min}$ );
3. Metrics computed from voice similarity matrices: de-identification and voice distinctiveness preservation;
4. Linkability;
5. Zero evidence biometric recognition assessment (ZEBRA) framework metrics: expected privacy disclosure (population) and worst case privacy disclosure (individual);
6. Word error rate (WER).

Metrics #1–5 were estimated using anonymized trial data, original or anonymized enrollment data, and  $ASV_{eval}$  or  $ASV_{eval}^{anon}$  models in different conditions corresponding to different attack models with increasing strength: *ignorant*, *lazy-informed*, and *semi-informed* (Tomashenko et al., 2021; Srivastava et al., submitted). The WER was computed on original or anonymized trial data using  $ASR_{eval}$  or  $ASR_{eval}^{anon}$ .

We consider the following **subjective evaluation** metrics:

1. Speaker verifiability: subjective speaker similarity (as well as metrics computed from the subjective speaker similarity scores (EER,  $C_{llr}$ ,  $C_{llr}^{min}$ ) and detection error trade-off (DET) curves);
2. Speaker linkability<sup>1</sup>;
3. Speech intelligibility;
4. Speech naturalness.

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<sup>1</sup>See (O'Brien et al., 2021) for more details.

## 2. Anonymization systems (summary)

Two different anonymization systems were provided as challenge baselines<sup>2</sup>:

- **B1** (primary baseline): extraction of pitch (F0) and bottleneck (BN) features followed by speech synthesis (SS) using an anonymized x-vector, an SS acoustic model (AM) and a neural source-filter (NSF) model (Tomashenko et al., 2020b; Srivastava et al., 2020a);
- **B2** (secondary baseline): anonymization using McAdams coefficient (Patino et al., 2021).

Table 1 provides an overview of the systems submitted by the challenge participants. Most systems were inspired by the primary baseline, one system was based upon the secondary baseline, and two systems are not related to either.

Table 1: Challenge submissions, team names and organizations. Submission identifiers (IDs) for each system are shown in the last column (ID) and comprise: <team id: first letter of the team name><submission deadline<sup>3</sup>: 1 or 2><c, if the system is contrastive><index of the contrastive system>. Blue star symbols  $\star$  in the first column indicate teams submitted the anonymized training data for post-evaluation analysis;  $\textcircled{1}$  and  $\textcircled{2}$  – teams developed their systems from the baseline-1 and baseline-2 respectively, and  $\textcircled{\phantom{1}}$  – other submissions.

Team (Reference)	System (Details)
AIS-lab JAIST (Mawalim et al., 2020) $\textcircled{A}$	<b>A1</b> (x-vector anonymization using variability-driven ensemble regression modeling) <b>A2</b> (using singular value modification)
DA-IICT Speech Group (Gupta et al., 2020) $\textcircled{D}$	<b>D1</b> (modifications to pole radius)
Idiap-NKI (Dubagunta et al., 2020) $\textcircled{I}$	<b>I1</b> (modifications to formants, F0 and speaking rate)
Kyoto Team (Han et al., 2020) $\textcircled{K}$ $\star$	<b>K2</b> (anonymization using x-vectors, SS models and a voice-indistinguishability metric)
MultiSpeech (Champion et al., 2020) $\textcircled{M}$ $\star$	<b>M1</b> (end-to-end ASR model for BN feature extraction) <b>M1c1</b> (semi-adversarial training to learn linguistic features while masking speaker information) <b>M1c2</b> (copy-synthesis (original x-vectors)) <b>M1c3</b> (x-vectors provided to SS AM are anonymized, x-vectors provided to NSF are original) <b>M1c4</b> (x-vectors provided to SS AM are original, x-vectors provided to NSF are anonymized)
Oxford System Security Lab (Turner et al., 2020) $\textcircled{O}$ $\star$	<b>O1</b> (keeping original distribution of cosine distances between speaker x-vectors; GMM for sampling x-vectors in a PCA-reduced space followed by projection to the original dimension) <b>O1c1</b> ( <b>O1</b> with forced dissimilarity between original and generated x-vectors)
Sigma Technologies SLU (Espinoza-Cuadros et al., 2020) $\textcircled{S}$ $\star$	<b>S1</b> ( <b>S1c1</b> applied on the top of the <b>B1</b> x-vector anonymization) <b>S1c1</b> (domain-adversarial training; autoencoders: using gender, accent, speaker id outputs corresponding to adversarial branches in the neural network for x-vector reconstruction) <b>S2</b> ( <b>S2c1</b> applied on the top of the <b>B1</b> x-vector anonymization) <b>S2c1</b> ( <b>S1c1</b> with parameter optimization)
PingAn (Huang, 2020)	a non-challenge entry work; this team worked on the development of stronger attack models for ASV evaluation.

## 3. Objective evaluation

This section presents objective evaluation results for the primary challenge metrics (Section 3.1), alternative metrics and attack models (Sections 3.2–3.6), as well as comparative results for different privacy metrics (Section 3.7).

<sup>2</sup>Baseline systems are available online: <https://github.com/Voice-Privacy-Challenge/Voice-Privacy-Challenge-2020>

<sup>3</sup>Deadline-1: 8th May 2020; deadline-2: 16th June 2020.

### 3.1. EER, $C_{\text{llr}}$ , and $C_{\text{llr}}^{\text{min}}$

**Equal error rate (EER).** Denoting by  $P_{\text{fa}}(\theta)$  and  $P_{\text{miss}}(\theta)$  the false alarm and miss rates at threshold  $\theta$ , the EER corresponds to the threshold  $\theta_{\text{EER}}$  at which the two detection error rates are equal, i.e.,  $\text{EER} = P_{\text{fa}}(\theta_{\text{EER}}) = P_{\text{miss}}(\theta_{\text{EER}})$ . We also considered ROC (receiver operating characteristic) convex hull (Provost & Fawcett, 2001) EER, or ROCCH-EER (Brummer, 2010) for experiments in Section 5. The ROCCH is obtained by interpolating between the points of the ROC curve.

**Log-likelihood-ratio cost function ( $C_{\text{llr}}$  and  $C_{\text{llr}}^{\text{min}}$ ).** The log-likelihood-ratio cost function ( $C_{\text{llr}}$ ) was proposed by Brümmer & Du Preez (2006) as an *application-independent* evaluation objective and is defined as follows:

$$C_{\text{llr}} = \frac{1}{2} \left( \frac{1}{N_{\text{tar}}} \sum_{i \in \text{tar}} \log_2 (1 + e^{-\text{LLR}_i}) + \frac{1}{N_{\text{imp}}} \sum_{j \in \text{imp}} \log_2 (1 + e^{\text{LLR}_j}) \right), \quad (1)$$

where  $N_{\text{tar}}$  and  $N_{\text{imp}}$  are respectively the number of target and impostor log-likelihood ratio (LLR) values in the evaluation set.  $C_{\text{llr}}$  can be decomposed into a discrimination loss ( $C_{\text{llr}}^{\text{min}}$ ) and a calibration loss ( $C_{\text{llr}} - C_{\text{llr}}^{\text{min}}$ ) (Brümmer & Du Preez, 2006). The  $C_{\text{llr}}^{\text{min}}$  is estimated by optimal calibration using monotonic transformation of scores to their empirical LLR values. To obtain this monotonic transformation, the pool adjacent violators (PAV) to LLR algorithm is used (Brümmer & Du Preez, 2006; Ramos & Gonzalez-Rodriguez, 2008).

$C_{\text{llr}}^{\text{min}}$  relates to the EER through the receiver operating characteristic (ROC) convex hull:  $C_{\text{llr}}^{\text{min}}$  is its scalar summary and the EER an extreme point (Brümmer & De Villiers, 2011). If the EER of the convex hull changes, the entire hull is affected due to convexity and hence is  $C_{\text{llr}}^{\text{min}}$ ; by contrast, a change in  $C_{\text{llr}}^{\text{min}}$  does not need to affect the EER.

**Results.** Tables 2 and 3 provide the privacy objective evaluation results in terms of EER,  $C_{\text{llr}}$ , and  $C_{\text{llr}}^{\text{min}}$  for two attack models — *ignorant* (**oa**: original enrollment and anonymized trial data) and *lazy-informed* (**aa**: anonymized enrollment and anonymized trial data) — on the VoicePrivacy development and test datasets for all submitted and baseline anonymization systems. Figures 1 and 2 provide the summary of EER and  $C_{\text{llr}}^{\text{min}}$  on the test datasets for ignorant and lazy-informed attack models.

### 3.2. Zero evidence biometric recognition assessment (ZEBRA) framework

**Expected and worst-case privacy disclosure.** Expected and worst-case privacy disclosure metrics have been proposed by Nautsch et al. (2020) for the zero evidence biometric recognition assessment (ZEBRA) framework. They measure the average level of privacy preservation afforded by a given safeguard for a population and the worst-case privacy disclosure for an individual. If the expected privacy disclosure  $D_{\text{ECE}}$  is equal to 0, then we assume that perfect privacy (zero evidence) is achieved.

**Results.** Expected and worst-case privacy disclosure results are given in Table 4 (development) and Table 5 (test) for ignorant and lazy-informed attack models. ZEBRA assessment empirical cross entropy (ECE) plots are shown in Figures 3, 4 (*LibriSpeech*) and Figures 5, 6 (*VCTK different*) in the form: (expected privacy disclosure, worst-case privacy disclosure, categorical tags of worst-case privacy disclosure).<sup>4</sup>

<sup>4</sup>Categorical tags of worst-case privacy disclosure (Nautsch et al., 2020)

Tag	Posterior odds ratio (flat prior)
0	50 : 50 (flat posterior)
A	more disclosure than 50 : 50
B	one wrong in 10 to 100
C	one wrong in 100 to 10 000
D	one wrong in 10 000 to 100 000
E	one wrong in 100 000 to 1 000 000
F	one wrong in at least 1 000 000

Table 2: Objective results: EER,  $C_{lr}$ , and  $C_{lr}^{\min}$  for ignorant and lazy-informed attack models on the development data. Larger EER and  $C_{lr}^{\min}$  values correspond to better privacy.

EER – Ignorant (oa)																					
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1	
LibriSpeech	female	8.66	46.88	51.85	50.14	35.23	33.10	31.25	43.32	50.99	50.71	25.57	50.43	26.42	43.32	43.89	45.88	43.32	43.47	44.32	
	male	1.24	54.19	59.01	57.76	18.17	19.72	15.37	41.93	53.88	54.97	24.07	54.66	24.22	50.31	49.69	50.00	54.35	40.37	49.84	
VCTK different	female	2.86	49.69	50.65	49.97	35.49	33.91	13.53	54.69	53.73	53.62	27.23	48.34	26.05	46.60	46.32	50.31	47.61	40.09	49.75	
	male	1.44	52.75	55.88	53.95	28.34	26.20	26.30	44.96	50.62	51.17	18.51	54.29	18.86	45.11	45.66	45.21	48.73	39.90	44.71	
VCTK common	female	2.62	48.55	50.58	49.71	34.01	32.56	18.60	47.38	50.58	51.16	29.94	48.84	30.23	44.77	46.80	50.58	47.09	45.06	50.58	
	male	1.43	51.85	57.83	54.99	23.93	24.50	29.06	49.29	53.28	53.28	21.37	54.13	21.94	49.29	49.86	47.58	48.43	42.45	48.15	

C <sub>lr</sub> – Ignorant (oa)																					
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1	
LibriSpeech	female	42.9	164.2	147.2	144.1	116.8	115.5	115.3	148.6	150.3	150.2	114.3	144.6	110.8	134.7	134.3	171.3	144.6	141.0	171.5	
	male	14.2	166.7	170.6	169.0	105.8	112.1	77.6	148.4	155.8	156.7	111.1	165.7	111.5	147.8	147.8	153.4	153.2	137.1	153.4	
VCTK different	female	1.1	173.5	164.3	166.0	90.6	102.5	23.6	181.4	178.1	173.8	113.8	159.7	118.4	168.0	167.3	179.3	163.1	153.4	177.9	
	male	1.2	162.1	166.5	167.5	98.5	101.2	75.1	138.6	161.9	162.7	104.9	163.8	108.1	154.8	155.2	152.0	153.2	144.5	151.3	
VCTK common	female	0.9	182.5	167.5	172.0	85.9	100.4	28.3	159.6	173.7	168.9	102.0	162.1	109.6	181.1	180.8	183.9	165.8	163.3	183.3	
	male	1.6	187.1	191.7	192.9	90.8	97.4	75.4	160.8	173.0	174.5	113.1	187.2	118.9	179.4	179.6	172.3	170.1	161.4	172.0	

C <sub>lr</sub> <sup>min</sup> – Ignorant (oa)																					
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1	
LibriSpeech	female	0.304	0.990	0.998	0.996	0.820	0.808	0.812	0.944	0.991	0.991	0.726	0.997	0.712	0.970	0.968	0.981	0.970	0.953	0.975	
	male	0.034	1.000	0.997	0.999	0.527	0.580	0.457	0.914	0.978	0.977	0.697	0.998	0.689	0.977	0.978	0.991	0.996	0.917	0.989	
VCTK different	female	0.100	0.969	0.988	0.989	0.907	0.898	0.443	1.000	0.996	0.993	0.748	0.985	0.731	0.945	0.944	0.963	0.970	0.893	0.958	
	male	0.052	1.000	1.000	1.000	0.743	0.731	0.712	0.978	0.999	0.997	0.613	1.000	0.630	0.990	0.992	0.991	0.998	0.958	0.988	
VCTK common	female	0.088	0.990	0.996	0.995	0.877	0.864	0.553	0.966	0.994	0.994	0.773	0.988	0.771	0.957	0.959	0.982	0.975	0.946	0.976	
	male	0.050	0.997	1.000	0.999	0.671	0.672	0.703	0.991	0.993	0.995	0.598	0.999	0.620	0.990	0.991	0.987	0.993	0.953	0.985	

C <sub>lr</sub> <sup>min</sup> – Lazy-informed (aa)																					
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1	
LibriSpeech	female	0.304	0.872	0.864	0.894	0.621	0.650	0.663	0.138	0.833	0.824	0.566	0.826	0.547	0.898	0.902	0.924	0.922	0.800	0.921	
	male	0.034	0.854	0.780	0.867	0.358	0.370	0.559	0.086	0.799	0.787	0.516	0.828	0.508	0.947	0.944	0.969	0.933	0.844	0.964	
VCTK different	female	0.100	0.771	0.770	0.760	0.503	0.452	0.505	0.166	0.696	0.722	0.376	0.708	0.376	0.838	0.826	0.834	0.713	0.503	0.829	
	male	0.052	0.836	0.738	0.839	0.385	0.435	0.388	0.304	0.858	0.876	0.346	0.823	0.347	0.938	0.936	0.898	0.887	0.806	0.881	
VCTK common	female	0.088	0.696	0.705	0.741	0.366	0.353	0.509	0.140	0.869	0.855	0.371	0.712	0.365	0.843	0.832	0.814	0.775	0.641	0.802	
	male	0.050	0.816	0.704	0.840	0.316	0.394	0.563	0.185	0.929	0.921	0.316	0.820	0.318	0.957	0.950	0.936	0.931	0.787	0.921	

Table 3: Objective results: EER,  $C_{lr}$ , and  $C_{lr}^{\min}$  for ignorant and lazy-informed attack models on the test data. Larger EER and  $C_{lr}^{\min}$  values correspond to better privacy.

EER – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	7.66	50.36	48.91	47.26	25.91	25.55	23.54	42.52	51.28	51.82	28.65	47.26	22.08	41.79	42.52	44.53	44.34	41.24	43.61
	male	1.11	50.56	54.34	52.12	17.82	17.15	18.49	45.21	54.79	54.57	19.82	52.12	19.6	49.22	49.67	46.1	47.22	40.53	45.43
VCTK different	female	4.89	50.46	49.49	48.05	30.09	29.53	29.53	60.44	52.62	52.62	25.87	45.68	26.44	43.31	43.0	49.02	46.5	44.7	48.2
	male	2.07	51.89	54.25	53.85	28.24	27.38	35.82	58.78	55.57	56.08	23.65	53.73	24.28	46.67	47.53	48.34	47.24	43.92	48.22
VCTK common	female	2.89	50.87	48.55	48.27	30.64	29.77	32.66	50.29	51.45	52.31	27.17	47.4	26.3	45.66	43.06	46.53	44.8	41.91	47.11
	male	1.13	52.54	55.65	53.39	24.29	27.68	29.1	57.06	53.67	52.82	17.23	53.11	16.67	46.33	46.61	45.76	45.48	38.42	44.92
EER – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	7.66	28.83	28.65	32.12	15.15	16.24	24.82	0.73	31.39	30.47	23.54	32.66	17.88	38.32	39.23	35.58	40.88	30.66	35.04
	male	1.11	35.41	30.96	36.75	8.24	8.91	14.92	4.23	32.29	32.07	16.93	36.30	17.82	40.98	42.54	46.99	39.87	36.75	46.33
VCTK different	female	4.89	30.81	32.92	31.74	16.92	18.42	26.34	3.04	28.81	29.94	13.07	29.63	15.23	32.97	32.82	35.08	30.97	27.73	34.10
	male	2.07	31.11	21.87	30.94	12.23	12.51	22.96	5.97	32.20	31.52	11.77	31.46	12.92	42.65	42.48	39.61	38.69	31.00	38.98
VCTK common	female	2.89	29.48	28.61	31.21	14.16	17.05	26.01	2.89	34.39	33.82	14.74	28.61	15.32	38.73	39.31	39.02	33.24	28.61	37.57
	male	1.13	27.40	20.34	31.07	12.15	12.99	13.84	5.65	35.59	36.72	6.50	29.94	7.63	42.37	42.37	38.70	37.85	28.25	37.57
C <sub>lr</sub> – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	26.8	165.1	151.9	151.8	115.5	119.5	94.6	155.7	156.0	155.5	112.3	147.8	110.9	145.5	146.8	166.8	144.0	143.7	168.5
	male	15.3	164.4	168.8	166.7	106.4	110.9	89.0	156.9	159.0	160.1	117.6	165.8	117.6	174.1	175.1	155.7	151.7	146.1	155.5
VCTK different	female	1.5	154.5	142.9	146.9	93.2	103.7	41.0	171.6	157.0	152.3	97.4	141.5	104.3	148.3	147.8	156.7	146.1	142.8	156.0
	male	1.8	163.7	164.8	167.8	101.6	111.9	79.4	162.6	166.0	169.2	111.3	165.9	111.6	162.5	162.6	157.6	156.2	152.2	157.5
VCTK common	female	0.9	170.4	157.7	162.5	94.0	107.9	51.9	170.6	176.8	171.9	91.6	155.7	99.6	161.6	160.7	172.0	157.7	152.9	171.7
	male	1.0	184.3	186.5	190.1	99.3	107.5	68.1	156.2	170.7	172.5	116.5	187.5	118.4	184.6	185.5	172.5	168.5	161.3	172.3
C <sub>lr</sub> – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	26.8	13.6	12.7	16.3	12.6	15.2	10.2	2.4	29.8	29.4	18.2	23.7	6.4	13.4	13.9	27.6	29.3	13.4	27.1
	male	15.3	28.0	24.2	33.9	15.4	21.9	10.7	4.8	41.5	38.3	10.3	33.4	10.6	17.6	19.2	48.3	44.8	39.2	47.7
VCTK different	female	1.5	13.6	11.3	11.5	41.3	49.7	11.9	1.6	30.3	30.6	6.5	10.1	7.1	17.8	18.1	21.9	15.1	12.2	21.3
	male	1.8	19.5	13.3	23.8	25.1	35.2	7.6	4.3	45.6	39.5	11.1	23.0	12.0	14.4	14.7	33.9	41.3	30.4	33.5
VCTK common	female	0.9	10.2	8.8	9.0	42.7	47.4	13.2	3.0	24.1	23.9	6.2	8.1	6.1	11.4	11.5	17.7	12.4	10.0	17.3
	male	1.0	15.6	9.8	21.7	28.2	36.1	5.3	7.4	34.5	33.1	6.8	21.0	7.3	10.4	10.7	32.1	34.0	21.9	30.6
C <sub>lr</sub> <sup>min</sup> – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.183	0.994	0.996	0.995	0.684	0.692	0.618	0.936	0.996	0.997	0.697	0.987	0.632	0.969	0.973	0.980	0.975	0.955	0.972
	male	0.041	0.997	1.000	0.999	0.499	0.491	0.498	0.898	0.997	0.999	0.608	0.999	0.601	0.983	0.982	0.985	0.983	0.935	0.981
VCTK different	female	0.169	1.000	0.999	0.998	0.794	0.798	0.742	1.000	1.000	0.999	0.719	0.993	0.741	0.981	0.978	0.996	0.992	0.984	0.996
	male	0.072	1.000	1.000	1.000	0.720	0.729	0.853	0.989	1.000	1.000	0.687	1.000	0.680	0.992	0.991	0.996	0.996	0.981	0.996
VCTK common	female	0.091	0.989	0.991	0.994	0.808	0.799	0.770	0.996	0.999	0.998	0.733	0.989	0.738	0.976	0.978	0.982	0.976	0.946	0.982
	male	0.036	0.999	1.000	1.000	0.713	0.720	0.699	0.973	0.998	0.998	0.514	1.000	0.508	0.988	0.987	0.987	0.990	0.941	0.985
C <sub>lr</sub> <sup>min</sup> – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.183	0.765	0.777	0.839	0.491	0.512	0.592	0.025	0.838	0.813	0.639	0.843	0.532	0.915	0.928	0.897	0.901	0.792	0.886
	male	0.041	0.878	0.806	0.903	0.264	0.279	0.434	0.133	0.840	0.821	0.521	0.898	0.549	0.960	0.966	0.979	0.939	0.910	0.978
VCTK different	female	0.169	0.842	0.871	0.847	0.547	0.580	0.752	0.113	0.810	0.823	0.443	0.803	0.487	0.861	0.859	0.896	0.836	0.781	0.882
	male	0.072	0.849	0.666	0.834	0.398	0.424	0.666	0.226	0.863	0.863	0.396	0.841	0.431	0.968	0.965	0.954	0.943	0.833	0.947
VCTK common	female	0.091	0.783	0.800	0.830	0.464	0.500	0.698	0.095	0.887	0.877	0.438	0.775	0.458	0.910	0.903	0.919	0.875	0.792	0.913
	male	0.036	0.769	0.614	0.835	0.354	0.388	0.453	0.202	0.904	0.883	0.218	0.815	0.245	0.957	0.960	0.943	0.923	0.800	0.927

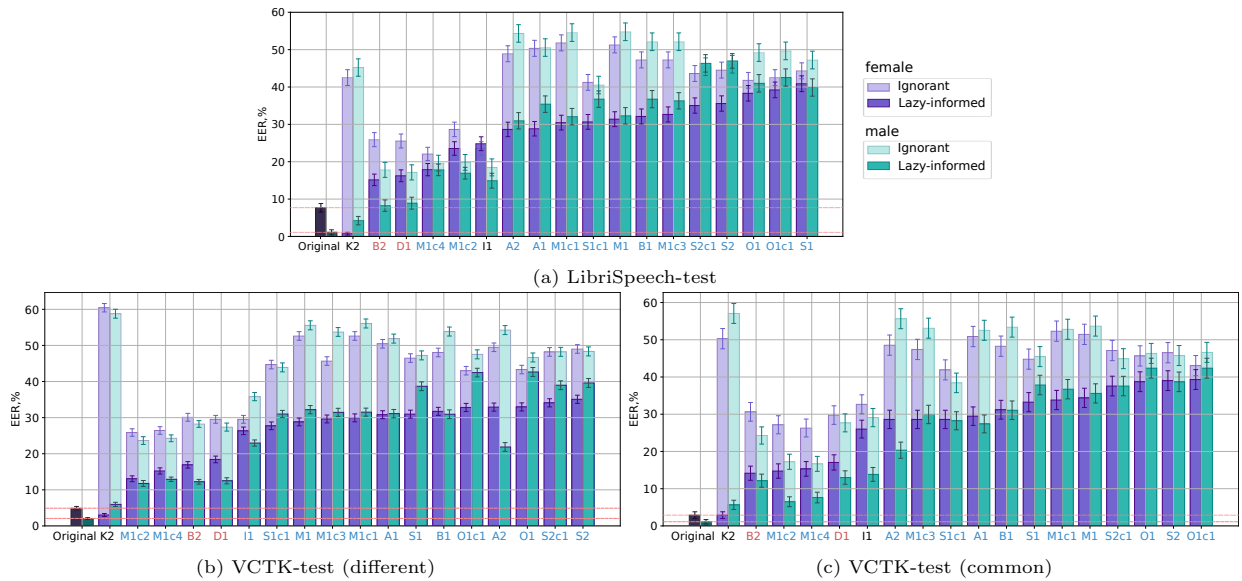


Figure 1: EER results (with 95% confidence intervals computed as proposed by (Bengio & Mariéthoz, 2004)) on the test datasets for different anonymization systems and for original data. Blue and red colors in the system notations indicate systems developed from B1 and B2 respectively. The results are ordered by EER values on female speakers for the lazy-informed attack model. Larger EER values correspond to better privacy.

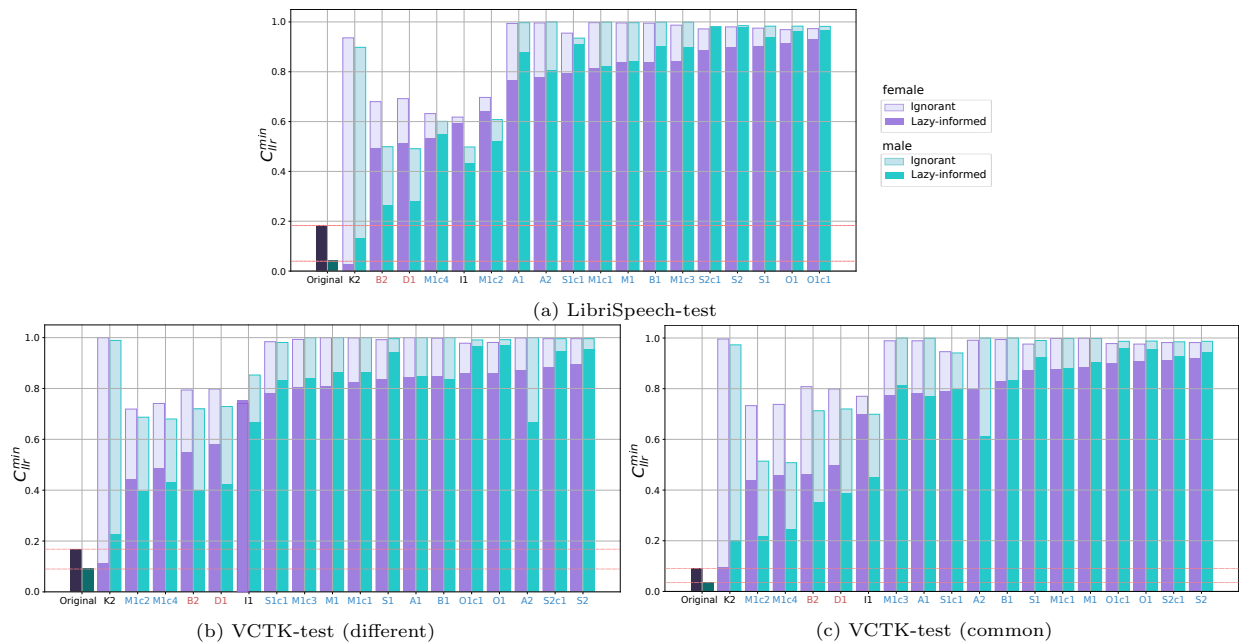


Figure 2:  $C_{llr}^{min}$  results on the test datasets for different anonymization systems and for original data; **oa**: original enrollment and anonymized trial data; **aa**: both enrolment and trial data are anonymized. Blue and red colors in the system notations indicate systems developed from B1 and B2 respectively. The results are ordered by  $C_{llr}^{min}$  values on female speakers for the lazy-informed attack model. Larger  $C_{llr}^{min}$  values correspond to better privacy.



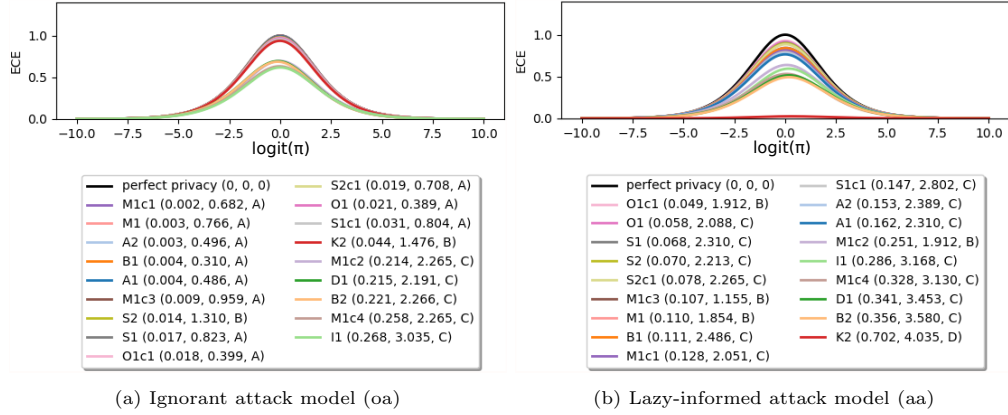


Figure 3: ZEBRA assessment with ECE profiles on *LibriSpeech-test* for female speakers.

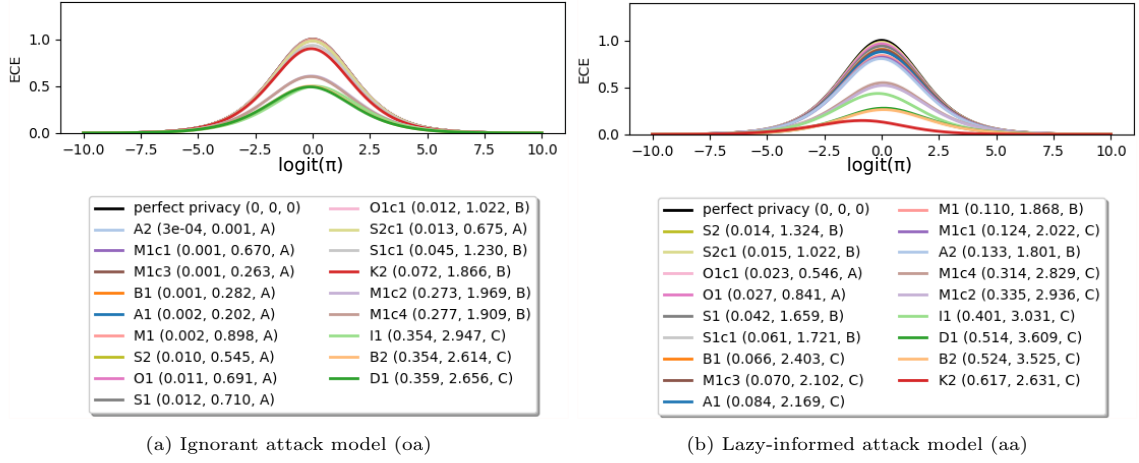


Figure 4: ZEBRA assessment with ECE profiles on *LibriSpeech-test* for male speakers.

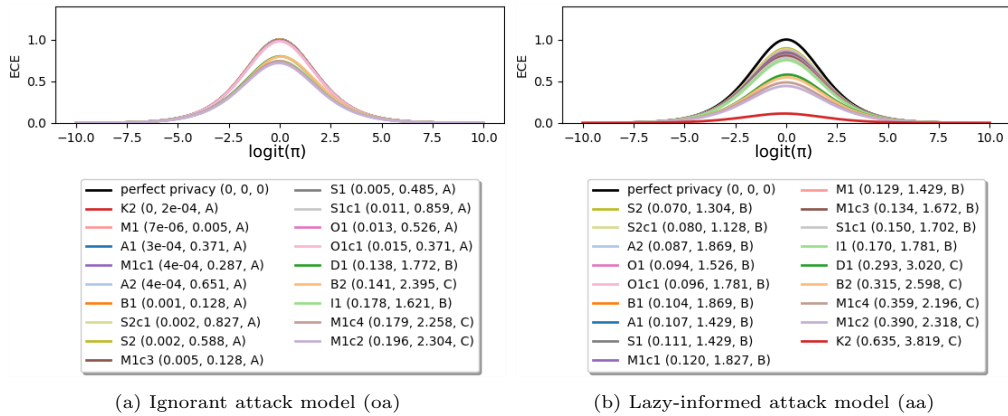


Figure 5: ZEBRA assessment with ECE profiles on *VCTK-test (different)* for female speakers.

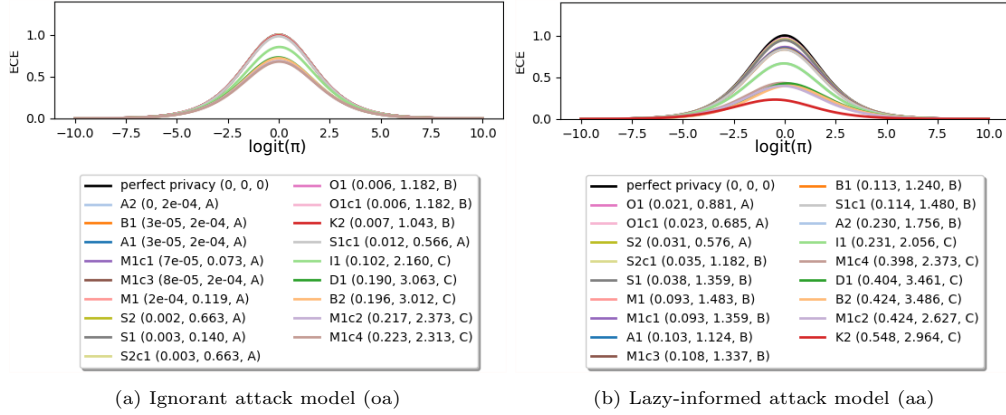


Figure 6: ZEBRA assessment with ECE profiles on *VCTK-test (different)* for male speakers.

Table 4: Objective results: ZEBRA expected and worst-case privacy disclosure for ignorant and lazy-informed attack models on the development data.

ZEBRA: Expected privacy disclosure (population), bit – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.492	0.007	0.002	0.002	0.126	0.135	0.129	0.038	0.006	0.006	0.190	0.002	0.201	0.020	0.022	0.013	0.020	0.033	0.017
	male	0.696	0.000	0.002	0.001	0.334	0.295	0.383	0.060	0.016	0.016	0.211	0.001	0.216	0.016	0.015	0.006	0.002	0.058	0.008
VCTK different	female	0.646	0.021	0.008	0.008	0.063	0.069	0.391	0.000	0.003	0.005	0.174	0.010	0.186	0.038	0.039	0.025	0.021	0.075	0.029
	male	0.682	0.000	0.000	0.000	0.178	0.186	0.200	0.015	0.001	0.002	0.267	0.000	0.254	0.006	0.005	0.006	0.001	0.028	0.008
VCTK common	female	0.653	0.007	0.003	0.004	0.083	0.093	0.311	0.023	0.004	0.004	0.159	0.008	0.160	0.030	0.029	0.013	0.017	0.038	0.017
	male	0.683	0.002	0.000	0.001	0.228	0.229	0.207	0.006	0.005	0.004	0.282	0.001	0.266	0.007	0.006	0.009	0.005	0.032	0.010
ZEBRA: Expected privacy disclosure (population), bit – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.492	0.087	0.092	0.072	0.267	0.246	0.237	0.614	0.115	0.121	0.305	0.121	0.318	0.069	0.067	0.052	0.053	0.139	0.053
	male	0.696	0.100	0.151	0.091	0.452	0.444	0.310	0.654	0.138	0.146	0.341	0.119	0.346	0.036	0.038	0.021	0.045	0.109	0.025
VCTK different	female	0.646	0.156	0.157	0.164	0.349	0.385	0.346	0.595	0.209	0.191	0.440	0.200	0.440	0.110	0.119	0.113	0.198	0.351	0.116
	male	0.682	0.111	0.180	0.110	0.433	0.398	0.436	0.492	0.096	0.084	0.461	0.121	0.460	0.042	0.043	0.069	0.076	0.132	0.081
VCTK common	female	0.653	0.210	0.203	0.179	0.447	0.457	0.344	0.614	0.089	0.098	0.446	0.199	0.450	0.107	0.115	0.127	0.154	0.252	0.136
	male	0.683	0.127	0.207	0.110	0.487	0.429	0.306	0.579	0.048	0.054	0.483	0.124	0.482	0.029	0.034	0.043	0.047	0.148	0.053
ZEBRA: worst-case privacy disclosure (individual) – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	3.829	0.629	0.344	0.310	3.129	3.219	2.161	1.301	0.556	0.948	2.082	0.435	2.112	0.737	1.617	1.316	0.976	1.455	1.015
	male	4.055	0.016	0.476	0.258	3.062	3.046	3.622	1.620	1.386	1.354	2.124	0.355	2.298	0.984	0.997	0.786	0.997	1.775	0.956
VCTK different	female	3.972	1.473	1.059	1.570	1.825	1.318	2.908	0.171	1.172	0.929	2.192	0.999	2.193	1.752	1.478	1.221	1.472	2.118	1.524
	male	4.037	0.332	0.000	0.000	1.888	1.818	3.312	1.444	0.411	0.291	2.064	0.270	2.020	0.134	0.383	0.145	0.168	1.110	0.188
VCTK common	female	3.596	0.845	0.322	0.229	1.447	1.748	2.100	0.628	0.294	0.434	1.808	0.515	1.991	1.117	1.212	0.763	0.706	1.201	0.837
	male	3.616	1.322	0.067	0.368	1.924	2.447	2.779	0.434	1.146	0.602	2.608	0.669	2.488	0.535	0.845	1.146	0.477	1.447	1.447
ZEBRA: worst-case privacy disclosure (individual) – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	3.829	1.617	1.617	2.094	3.531	3.520	3.208	2.815	2.094	2.316	2.677	2.069	3.023	1.839	2.094	1.617	1.219	2.520	1.793
	male	4.055	1.900	1.738	1.951	3.673	3.684	3.415	3.190	1.979	2.502	3.014	1.997	2.889	0.934	0.868	0.821	1.298	2.076	0.997
VCTK different	female	3.972	1.180	1.800	1.473	3.232	3.389	3.088	3.359	2.504	2.149	2.881	1.774	2.998	1.328	1.707	1.237	2.141	2.884	1.415
	male	4.037	1.446	1.851	1.462	3.549	3.316	3.773	3.156	1.411	1.110	2.626	1.779	2.623	1.110	1.110	1.508	1.622	1.809	1.353
VCTK common	female	3.596	1.498	1.690	1.514	2.845	2.779	2.376	3.298	1.447	1.447	3.100	1.924	2.972	1.845	1.447	1.393	1.447	2.100	1.499
	male	3.616	1.447	1.753	1.748	2.862	2.508	2.997	2.479	1.447	1.623	2.294	1.690	2.322	1.146	1.146	0.845	1.322	1.773	1.146

Table 5: Objective results: ZEBRA expected and worst-case privacy disclosure for ignorant and lazy-informed attack models on the test data.

ZEBRA: Expected privacy disclosure (population), bit – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.584	0.004	0.003	0.004	0.221	0.215	0.268	0.044	0.003	0.002	0.213	0.009	0.257	0.021	0.018	0.014	0.017	0.031	0.019
	male	0.690	0.002	0.000	0.001	0.354	0.359	0.353	0.072	0.002	0.001	0.272	0.001	0.277	0.011	0.012	0.010	0.012	0.045	0.013
VCTK different	female	0.594	0.000	0.000	0.001	0.141	0.138	0.178	0.000	0.000	0.000	0.195	0.005	0.179	0.013	0.015	0.003	0.005	0.011	0.002
	male	0.667	0.000	0.000	0.000	0.196	0.190	0.101	0.007	0.000	0.000	0.217	0.000	0.222	0.006	0.006	0.002	0.003	0.012	0.003
VCTK common	female	0.653	0.007	0.006	0.004	0.132	0.138	0.161	0.003	0.001	0.001	0.185	0.007	0.181	0.016	0.015	0.013	0.017	0.037	0.012
	male	0.694	0.001	0.000	0.000	0.199	0.196	0.212	0.019	0.001	0.001	0.341	0.000	0.346	0.008	0.009	0.009	0.007	0.040	0.010
ZEBRA: Expected privacy disclosure (population), bit – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.584	0.162	0.153	0.111	0.356	0.341	0.286	0.702	0.110	0.128	0.250	0.107	0.327	0.058	0.049	0.071	0.068	0.146	0.078
	male	0.690	0.084	0.133	0.066	0.524	0.514	0.401	0.617	0.110	0.123	0.335	0.070	0.315	0.027	0.023	0.015	0.042	0.061	0.015
VCTK different	female	0.594	0.107	0.087	0.104	0.315	0.293	0.170	0.635	0.129	0.120	0.390	0.135	0.359	0.094	0.096	0.071	0.111	0.150	0.080
	male	0.667	0.103	0.230	0.113	0.424	0.404	0.231	0.548	0.093	0.093	0.424	0.108	0.399	0.021	0.023	0.031	0.038	0.114	0.035
VCTK common	female	0.653	0.149	0.136	0.117	0.377	0.352	0.210	0.648	0.077	0.083	0.397	0.155	0.383	0.062	0.067	0.055	0.085	0.142	0.059
	male	0.694	0.159	0.268	0.113	0.458	0.434	0.384	0.568	0.065	0.079	0.558	0.126	0.538	0.029	0.027	0.039	0.053	0.137	0.049
ZEBRA: worst-case privacy disclosure (individual) – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	3.979	0.486	0.496	0.310	2.266	2.191	3.035	1.476	0.766	0.657	2.288	0.962	2.265	0.389	0.399	1.310	0.823	0.804	0.708
	male	3.924	0.202	0.001	0.282	2.614	2.656	2.947	1.866	0.956	0.721	1.966	0.302	1.908	0.691	1.022	0.545	0.710	1.217	0.662
VCTK different	female	3.655	0.371	0.651	0.128	2.395	1.772	1.617	0.000	0.005	0.319	2.304	0.127	2.274	0.526	0.371	0.625	0.485	0.854	0.827
	male	3.921	0.000	0.000	0.000	3.012	3.063	2.160	1.043	0.119	0.073	2.413	0.000	2.344	1.182	1.182	0.663	0.140	0.566	0.663
VCTK common	female	3.557	0.423	0.741	0.668	1.197	1.153	2.187	0.386	0.102	0.095	2.187	0.367	2.100	0.470	0.559	1.447	0.706	1.117	1.146
	male	3.675	0.447	0.192	0.447	2.488	2.690	2.909	1.204	0.243	0.183	2.468	0.544	2.401	0.544	1.146	0.380	0.669	0.720	0.392
ZEBRA: worst-case privacy disclosure (individual) – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	3.979	2.310	2.389	2.486	3.580	3.453	3.174	4.035	1.854	2.051	1.912	1.131	3.143	2.088	1.912	2.213	2.310	2.802	2.265
	male	3.924	2.169	1.801	2.403	3.525	3.609	3.031	2.631	1.868	2.022	2.936	2.102	2.829	0.841	0.546	1.022	1.659	1.721	0.926
VCTK different	female	3.655	1.429	1.869	1.869	2.598	3.020	1.781	3.819	1.429	1.827	2.290	1.656	2.204	1.526	1.781	1.304	1.429	1.702	1.128
	male	3.921	1.124	1.756	1.240	3.486	3.461	2.056	2.964	1.483	1.359	2.619	1.315	2.359	0.881	0.685	0.564	1.359	1.487	1.182
VCTK common	female	3.557	1.447	1.748	1.447	2.216	2.488	2.187	3.141	1.447	1.146	2.267	1.748	2.270	1.172	1.208	1.447	0.845	1.229	1.447
	male	3.675	1.447	1.857	1.447	3.080	2.702	2.157	2.593	1.021	1.447	2.902	1.170	2.561	0.869	1.146	0.502	1.146	1.447	0.618

### 3.3. Linkability

The *linkability* metric was proposed by Gomez-Barrero et al. (2017) for biometric template protection systems<sup>5</sup> and has been recently applied for the speech anonymization task by Maouche et al. (2020).

According to Gomez-Barrero et al. (2017), the local measure denoted  $D_{\leftrightarrow}(s) \in [0, 1]$  — a system score-wise linkability, evaluates the linkability of a system for a given specific linkage score. The local linkability metric for score  $s$  is defined as

$$D_{\leftrightarrow}(s) = \max\{0, p(H|s) - p(\bar{H}|s)\}, \quad (2)$$

where variables  $H$  and  $\bar{H}$  express whether two random utterances belong to the same speaker (*target*) or to different speakers (*impostor*) respectively.

The global linkability metric  $D_{\leftrightarrow}^{\text{sys}}$  is calculated over all target scores:

$$D_{\leftrightarrow}^{\text{sys}} = \int p(s|H) \cdot D_{\leftrightarrow}(s) ds. \quad (3)$$

The global linkability metric  $D_{\leftrightarrow}^{\text{sys}} \in [0, 1]$  provides an estimation of the global linkability of a system across all scores. It evaluates how non-overlapping are the score distributions of target and impostor pairs. A

<sup>5</sup>Definition of linkability (Gomez-Barrero et al., 2017): “two templates are fully linkable if there exists some method to decide that they were extracted, with all certainty, from the same biometric instance. Two templates are linkable to a certain degree if there exists some method to decide that it is more likely that they were extracted from the same instance than from different instances.”

linkability value of 0 means that the two distributions are indistinguishable, hence scores cannot be exploited by attackers and perfect privacy is achieved.

One advantage of the linkability metrics in comparison to EER is its threshold independence. Another interesting property of this metric is the possibility to detect any local separation between same-speaker and different-speaker scores.

**Results.** Tables 6 and 7 present the linkability values for ignorant and lazy-informed attackers on the development and test datasets. Linkability plots with target/impostor score distributions for the three attack models are shown in Figure 7.

Table 6: Objective results: Linkability for ignorant and lazy-informed attack models on the development data.

Linkability – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.801	0.076	0.067	0.088	0.258	0.299	0.326	0.132	0.085	0.085	0.376	0.052	0.389	0.105	0.108	0.089	0.111	0.099	0.093
	male	0.974	0.082	0.128	0.105	0.563	0.519	0.681	0.156	0.107	0.117	0.420	0.096	0.431	0.074	0.092	0.063	0.085	0.141	0.066
VCTK different	female	0.931	0.102	0.064	0.059	0.215	0.237	0.667	0.084	0.074	0.078	0.371	0.061	0.393	0.114	0.108	0.120	0.073	0.158	0.118
	male	0.968	0.058	0.081	0.069	0.354	0.375	0.476	0.092	0.053	0.055	0.566	0.068	0.565	0.075	0.072	0.069	0.044	0.138	0.083
VCTK common	female	0.935	0.055	0.048	0.084	0.246	0.262	0.593	0.142	0.049	0.065	0.311	0.063	0.304	0.093	0.094	0.082	0.073	0.116	0.089
	male	0.963	0.094	0.114	0.094	0.434	0.416	0.464	0.106	0.074	0.062	0.513	0.074	0.498	0.067	0.054	0.063	0.056	0.111	0.077
Linkability – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.801	0.260	0.268	0.223	0.498	0.485	0.438	0.894	0.272	0.296	0.535	0.262	0.553	0.219	0.206	0.160	0.230	0.304	0.161
	male	0.974	0.261	0.331	0.245	0.757	0.748	0.577	0.932	0.350	0.360	0.593	0.284	0.599	0.121	0.124	0.095	0.150	0.225	0.107
VCTK different	female	0.931	0.368	0.378	0.387	0.634	0.667	0.617	0.886	0.459	0.430	0.733	0.442	0.730	0.281	0.289	0.285	0.408	0.576	0.292
	male	0.968	0.306	0.402	0.300	0.745	0.683	0.703	0.766	0.282	0.270	0.748	0.318	0.744	0.152	0.156	0.229	0.236	0.328	0.251
VCTK common	female	0.935	0.415	0.414	0.364	0.731	0.732	0.582	0.885	0.260	0.271	0.711	0.402	0.708	0.256	0.275	0.294	0.331	0.438	0.302
	male	0.963	0.279	0.370	0.245	0.746	0.686	0.595	0.852	0.168	0.178	0.754	0.274	0.744	0.125	0.116	0.150	0.140	0.290	0.171

Table 7: Objective results: Linkability for ignorant and lazy-informed attack models on the test data.

Linkability – Ignorant (oa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.898	0.067	0.075	0.076	0.412	0.402	0.496	0.163	0.081	0.078	0.385	0.090	0.479	0.122	0.122	0.101	0.099	0.133	0.096
	male	0.958	0.074	0.085	0.083	0.578	0.579	0.654	0.142	0.083	0.089	0.527	0.082	0.521	0.085	0.071	0.084	0.101	0.141	0.086
VCTK different	female	0.881	0.045	0.050	0.056	0.379	0.359	0.370	0.172	0.062	0.060	0.393	0.069	0.375	0.091	0.091	0.042	0.060	0.077	0.046
	male	0.950	0.055	0.073	0.059	0.375	0.371	0.270	0.191	0.087	0.082	0.454	0.064	0.461	0.062	0.059	0.049	0.053	0.084	0.045
VCTK common	female	0.924	0.084	0.062	0.075	0.301	0.305	0.322	0.097	0.054	0.076	0.363	0.081	0.367	0.081	0.092	0.066	0.078	0.118	0.063
	male	0.972	0.079	0.099	0.074	0.420	0.388	0.417	0.173	0.072	0.070	0.584	0.082	0.577	0.057	0.078	0.069	0.072	0.159	0.082
Linkability – Lazy-informed (aa)																				
Data	Gender	Orig	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	0.898	0.346	0.355	0.295	0.666	0.654	0.587	0.962	0.298	0.320	0.542	0.319	0.603	0.183	0.164	0.223	0.278	0.305	0.238
	male	0.958	0.217	0.281	0.192	0.800	0.779	0.625	0.873	0.274	0.293	0.616	0.200	0.591	0.124	0.106	0.073	0.134	0.190	0.090
VCTK different	female	0.881	0.295	0.275	0.281	0.604	0.571	0.394	0.920	0.347	0.331	0.675	0.323	0.638	0.253	0.253	0.220	0.296	0.351	0.235
	male	0.950	0.282	0.463	0.295	0.729	0.712	0.458	0.845	0.273	0.280	0.704	0.285	0.673	0.104	0.109	0.138	0.149	0.287	0.146
VCTK common	female	0.924	0.318	0.324	0.275	0.636	0.588	0.432	0.919	0.224	0.245	0.618	0.329	0.595	0.160	0.169	0.167	0.243	0.321	0.173
	male	0.972	0.349	0.495	0.276	0.723	0.689	0.638	0.839	0.197	0.233	0.820	0.304	0.800	0.097	0.111	0.151	0.172	0.330	0.182

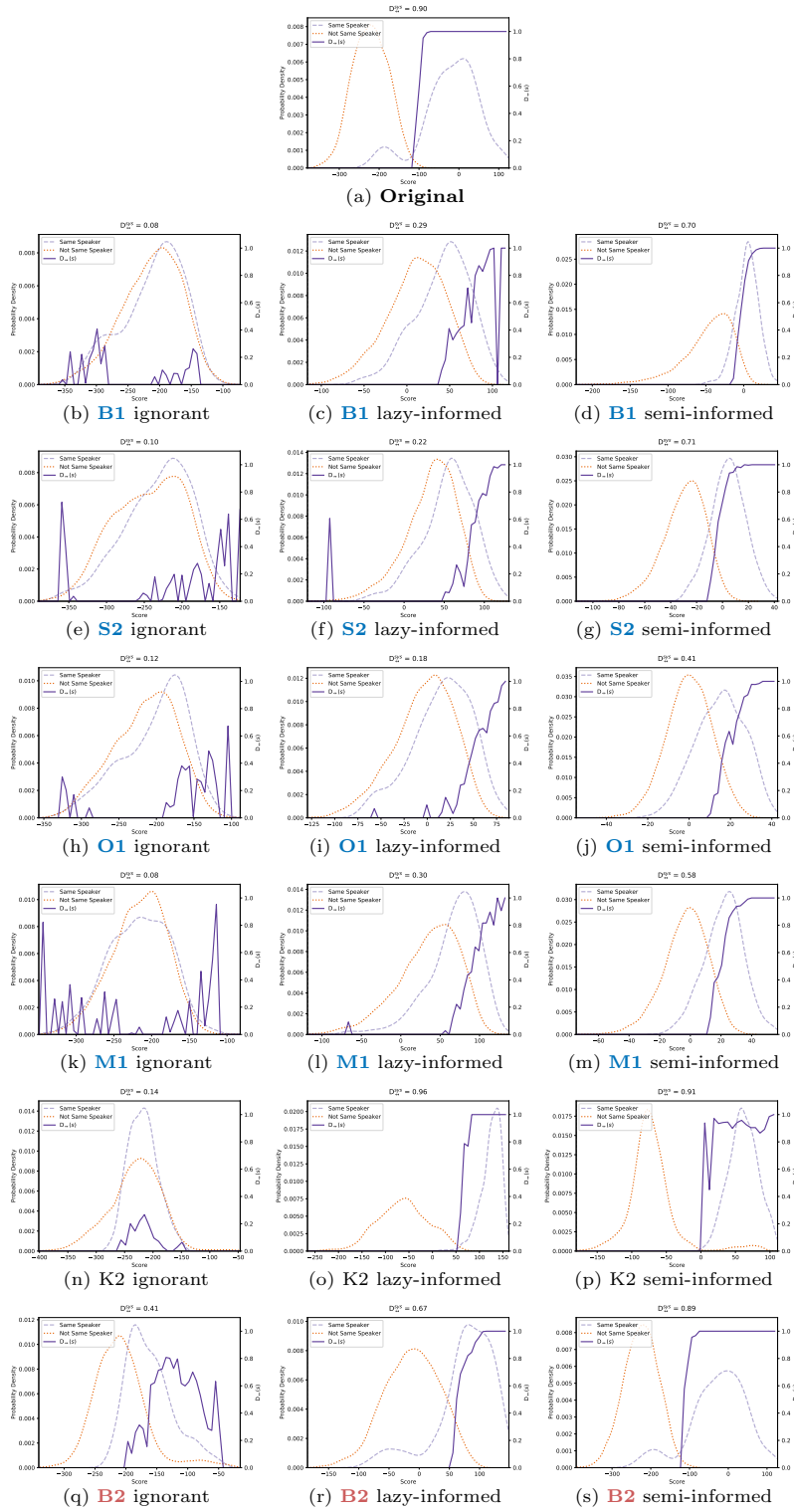


Figure 7: Female speaker linkability results on *LibriSpeech-test* computed for the selected set of primary anonymization systems.

### 3.4. Voice similarity matrices

To visualize anonymization performance across different speakers in a dataset, *voice similarity matrices* have been proposed by Noé et al. (2020). A voice similarity matrix  $M = (M(i, j))_{1 \leq i \leq N, 1 \leq j \leq N}$  is defined for a set of  $N$  speakers using similarity values  $M(i, j)$  computed for speakers  $i$  and  $j$  as follows:

$$M(i, j) = \text{sigmoid} \left( \frac{1}{n_i n_j} \sum_{\substack{1 \leq k \leq n_i, \text{ and } 1 \leq l \leq n_j \\ k \neq l \text{ if } i=j}} LLR(x_k^{(i)}, x_l^{(j)}) \right), \quad (4)$$

where  $LLR(x_k^{(i)}, x_l^{(j)})$  is the log-likelihood-ratio from the comparison of the  $k$ -th segment from the  $i$ -th speaker and the  $l$ -th segment from the  $j$ -th speaker,  $n_i, n_j$  are the numbers of segments for the corresponding speakers. Three types of matrices are computed:  $M_{oo}$  – on original data;  $M_{aa}$  – on anonymized data; and  $M_{oa}$  – on original and anonymized data. In the latter case, for computing  $M(i, j)$ , we use original data for speaker  $i$  and anonymized data for speaker  $j$ . A global matrix  $M$  is then constructed as

$$M = \begin{pmatrix} M_{oo} & M_{oa} \\ M_{oa} & M_{aa} \end{pmatrix}. \quad (5)$$

The voice similarity matrices shown in Figures 8, 9 for *LibriSpeech-test* and in Figures 10, 11 for *VCTK-test (different)* show substantial differences between the submitted systems. For  $M_{oo}$ , a distinct diagonal in the similarity matrix points out the speaker discrimination ability in the original set, while in  $M_{oa}$ , the diagonal disappears if the protection is good. In  $M_{aa}$ , the diagonal of the matrix emerges if the resulting pseudo-voices can be distinguished (Noé et al., 2020). The matrices for signal-processing based approaches (**B2, D1, I**) exhibit a distinct diagonal for  $M_{aa}$  matrices, indicating that voices remain distinguishable after anonymization. Among x-vector based systems, a distinct diagonal for  $M_{aa}$  is observed only for system **K2**. For system **M1c4**, where x-vectors provided to SS AM are original, a distinct diagonal is observed for  $M_{aa}$  and a less distinct one for  $M_{oa}$ . For x-vector based anonymization systems related to **B1**, no diagonal is observed for  $M_{oa}$  for all datasets which suggests high de-identification performance. System **K2** has the most distinct  $M_{aa}$  diagonal on *LibriSpeech-test* (Figures 8j and 9j), and confusions between some speaker voices can be seen only for male speakers (Figure 9j). For *VCTK-test (different)*, both matrices  $M_{oo}$  and  $M_{aa}$  have less distinct diagonals in comparison to *LibriSpeech-test*.

All the confusion matrices considered above were computed using the  $ASV_{\text{eval}}$  model trained on original (non-anonymized data). If we retrain the speaker verification model on the anonymized data and re-compute the confusion matrices using the obtained  $ASR_{\text{eval}}^{\text{anon}}$  model, we can observe in Figure 12 that the diagonals of the  $M_{aa}$  matrices become much more distinct. This means that the voice distinctiveness is better preserved with respect to the  $ASR_{\text{eval}}^{\text{anon}}$  model than with respect to  $ASR_{\text{eval}}$ .

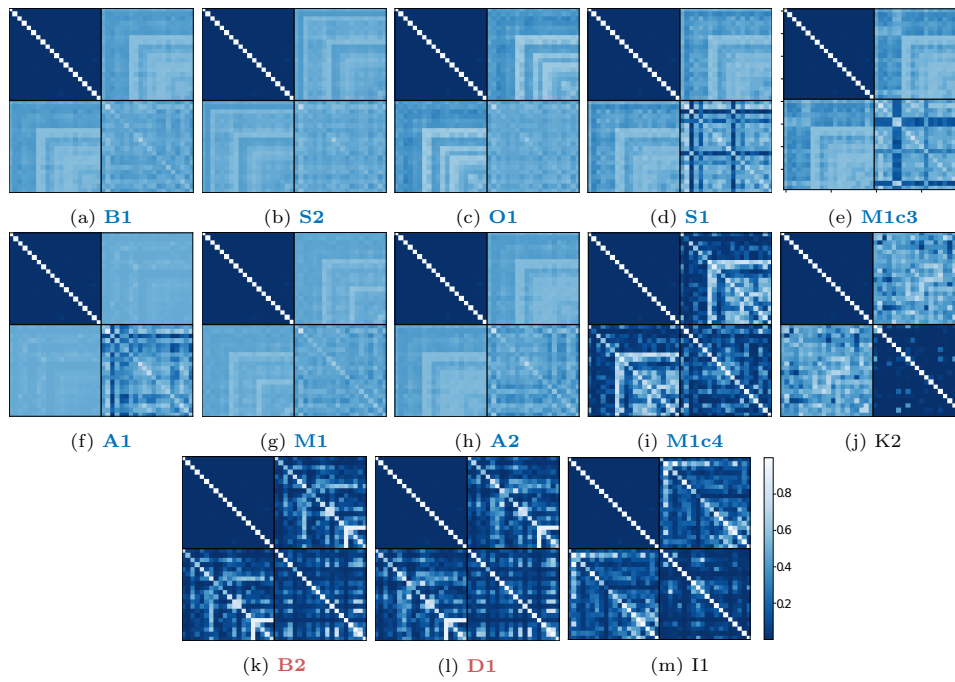


Figure 8: Voice similarity matrices on *LibriSpeech-test* for female speakers.

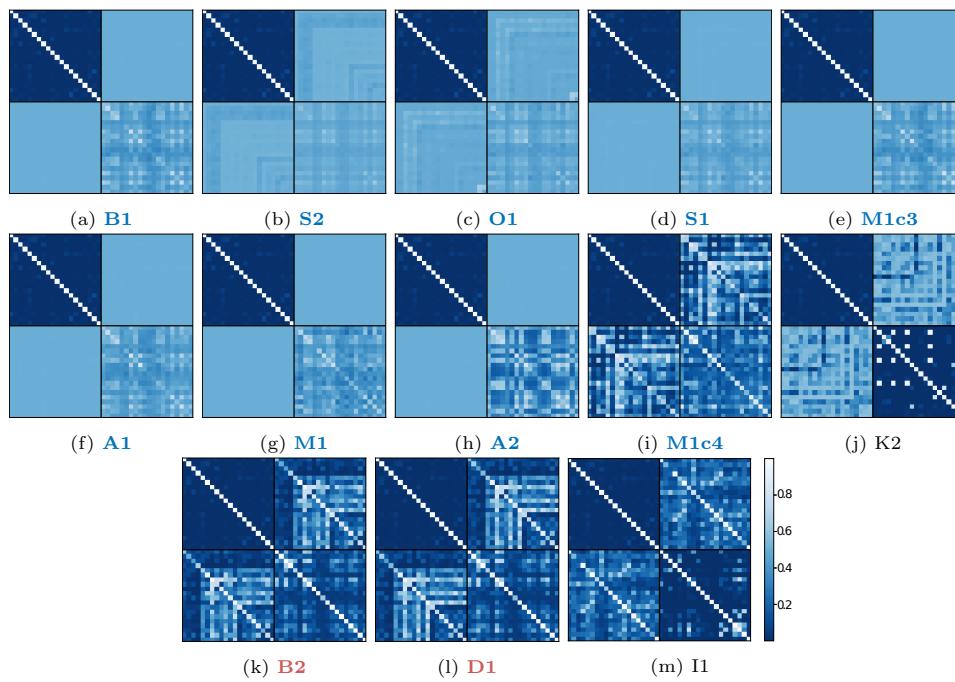


Figure 9: Voice similarity matrices on *LibriSpeech-test* for male speakers.

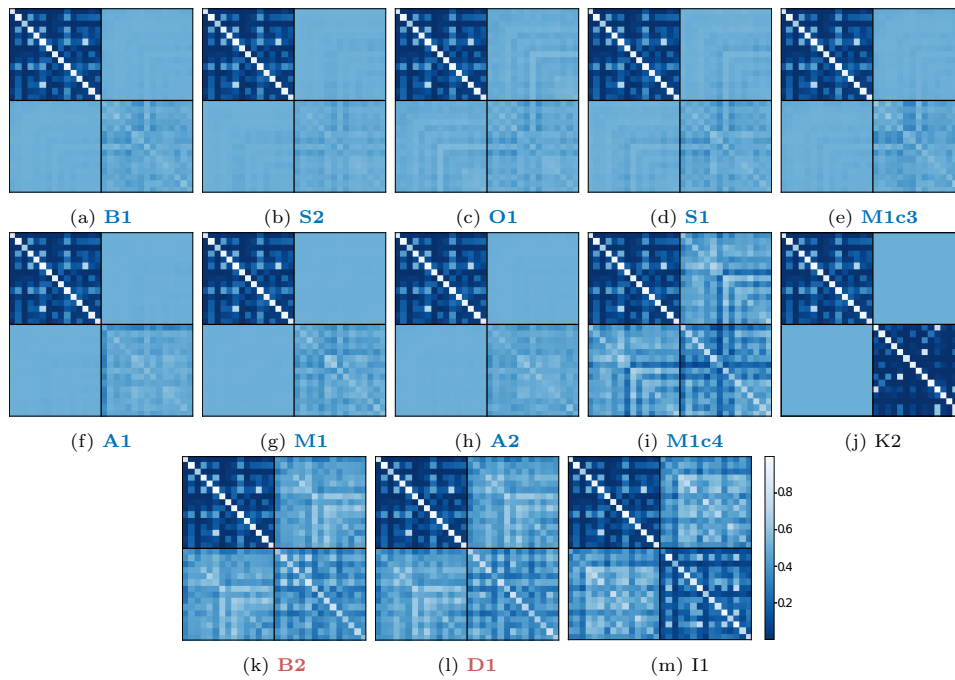


Figure 10: Voice similarity matrices on *VCTK-test (different)* for female speakers.

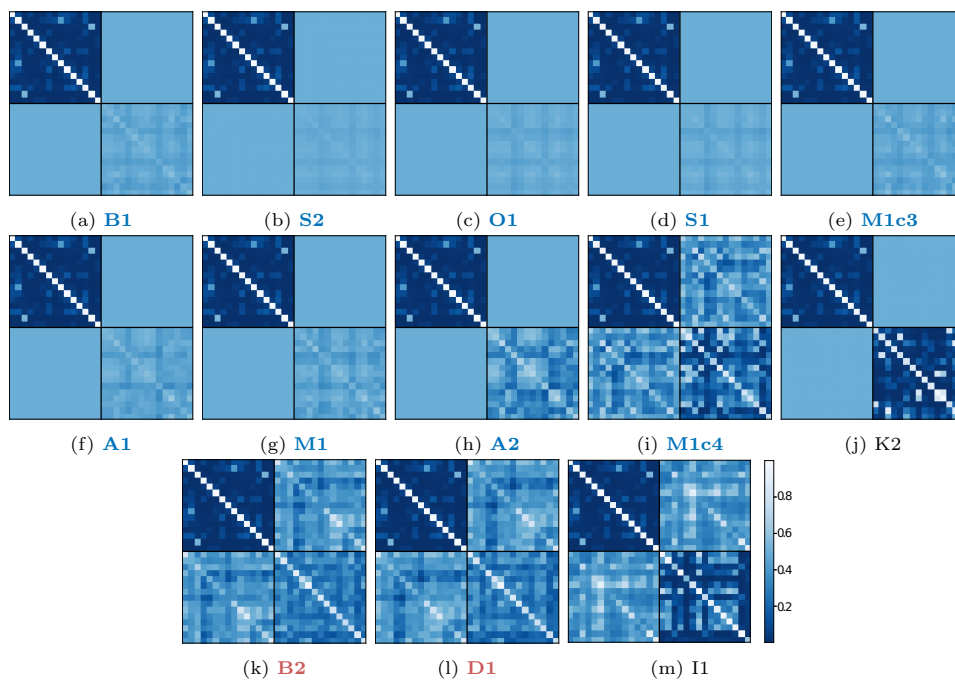


Figure 11: Voice similarity matrices on *VCTK-test (different)* for male speakers.



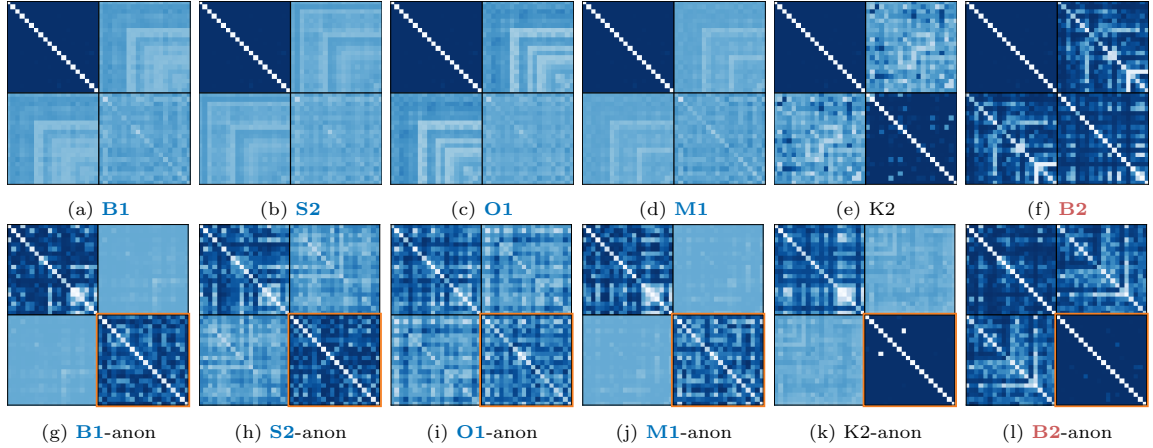


Figure 12: Comparison of voice similarity matrices computed with (1)  $ASV_{eval}$  trained on original data (upper row) and (2)  $ASV_{eval}^{anon}$  trained on anonymized speech data (lower row) on *LibriSpeech-test* computed for female speakers.

### 3.5. Gain of voice distinctiveness and de-identification

De-identification (DeID) and gain of voice distinctiveness ( $G_{VD}$ ) metrics are computed from voice similarity matrices (Noé et al., 2020, 2022). They are estimated based on the ratio of diagonal dominance for a pair of matrices  $\{M_{oa}, M_{oo}\}$  and  $\{M_{oo}, M_{oo}\}$  correspondingly. The diagonal dominance  $D_{diag}(M)$  is defined as the absolute difference between the mean values of diagonal and off-diagonal elements:<sup>6</sup>

$$D_{diag}(M) = \left| \sum_{1 \leq i \leq N} \frac{M(i, i)}{N} - \sum_{\substack{1 \leq j \leq N \\ \text{and } 1 \leq k \leq N \\ j \neq k}} \frac{M(j, k)}{N(N-1)} \right|. \quad (6)$$

**Gain of voice distinctiveness.** Gain of voice distinctiveness is defined as:

$$G_{VD} = 10 \log_{10} \frac{D_{diag}(M_{aa})}{D_{diag}(M_{oo})}, \quad (7)$$

where 0 means that the voice distinctiveness remains globally the same in the protected space, and gain above or below 0 corresponds respectively to increase or loss of global voice distinctiveness.

**De-identification.** De-identification is calculated as:

$$DeID = 1 - \frac{D_{diag}(M_{oa})}{D_{diag}(M_{oo})}. \quad (8)$$

$DeID = 100\%$  assumes perfect de-identification, while  $DeID = 0$  corresponds to a system which achieves no de-identification.

**Results.** *Gain of voice distinctiveness* ( $G_{VD}$ ) results are presented in Figure 13 and Tables 8, 9. Anonymization leads to the loss of voice distinctiveness for all (except **K2**) anonymization systems. Signal-processing based methods much better preserve voice distinctiveness than methods related to **B1** and the best results are achieved for methods **K2** and **I1**. There is a gap in performance between male and female speakers for most of the systems: for some anonymization methods,  $G_{VD}$  is higher for female speakers than for male (in particular, for **S2**, **S2c1**, and others), while for other methods (i.e. **A2**), on the contrary,  $G_{VD}$  is lower for female than for male speakers.

<sup>6</sup>See notations in Section 3.4

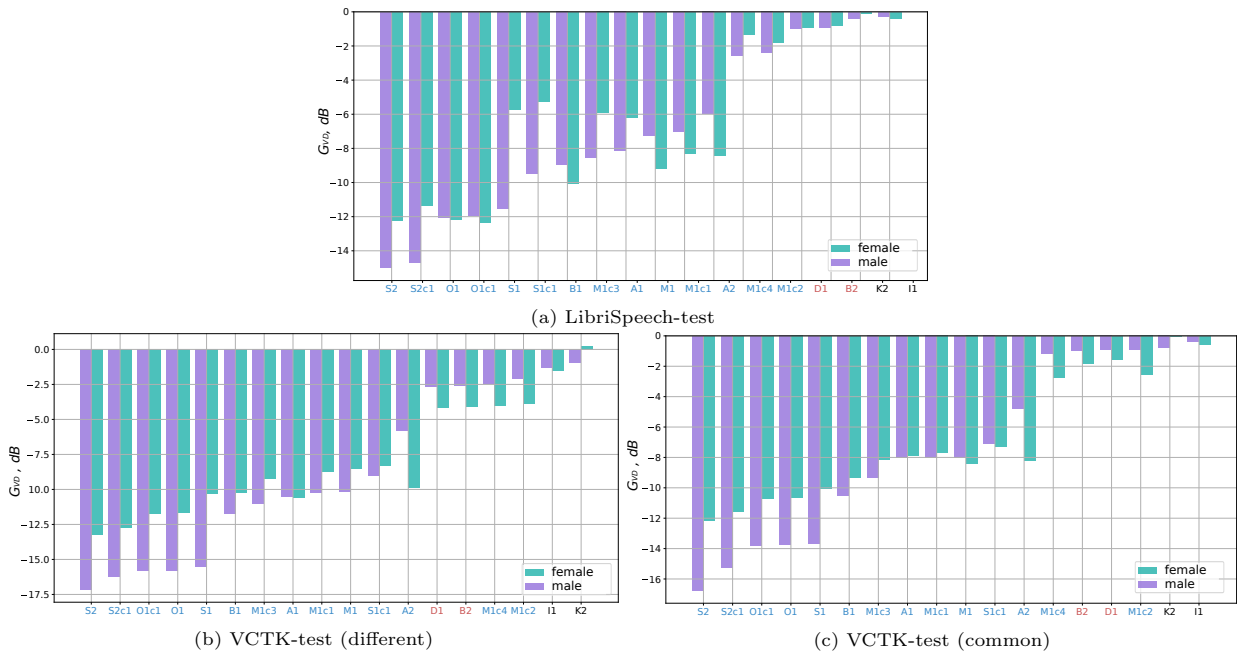


Figure 13: Gain of voice distinctiveness ( $G_{VD}$ ) results on the test datasets for different anonymization systems. Blue and red colors in the system notations indicate systems developed from B1 and B2, respectively. The results in each subfigure are ordered by metric values on male speakers. Higher  $G_{VD}$  values correspond to better voice distinctiveness preservation.

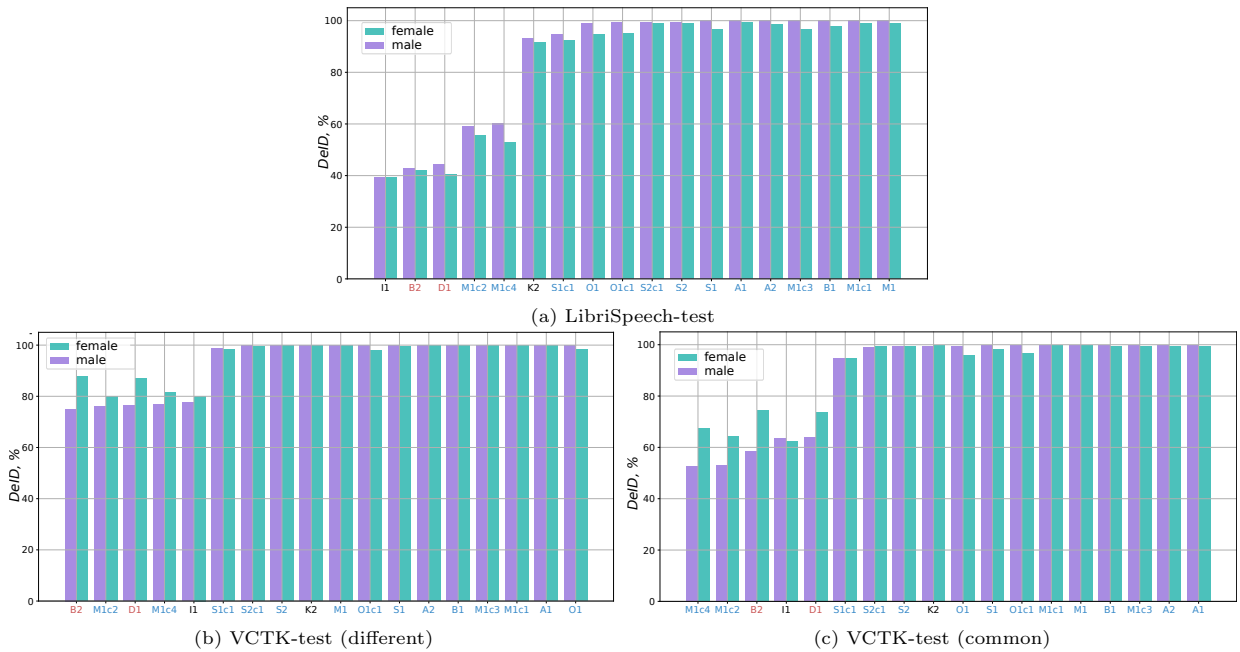


Figure 14: De-identification (DeID) results on the test datasets for different anonymization systems. Blue and red colors in the system notations indicate systems developed from B1 and B2, respectively. The results in each subfigure are ordered by metric values on male speakers. Higher DeID values correspond to better privacy.

Results for the *de-identification* (DeId) metric are shown in Figure 14 and Tables 8, 9. For most of the x-vector based anonymization methods almost full de-identification is achieved. In comparison with x-vector based anonymization methods, all signal-processing based techniques demonstrate a considerably lower level of de-identification.

Table 8: Objective results: Gain of voice distinctiveness ( $G_{VD}$ ) and De-identification (DeId) on the development data.

Gain of voice distinctiveness ( $G_{VD}$ )																			
Data	Gender	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	-8.48	-8.09	-9.17	-1.06	-1.15	-0.99	-0.29	-8.14	-7.69	-1.81	-6.85	-1.38	-12.03	-11.96	-12.64	-5.72	-5.01	-11.90
	male	-7.93	-6.02	-8.76	-1.19	-1.26	-0.33	-0.20	-7.58	-7.16	-2.07	-7.28	-2.18	-13.36	-13.22	-14.81	-11.62	-7.55	-14.13
VCTK different	female	-8.85	-8.48	-8.81	-3.61	-3.24	-1.06	-0.45	-7.58	-7.81	-2.96	-7.69	-3.14	-8.95	-8.91	-10.33	-6.64	-5.02	-9.82
	male	-13.36	-8.86	-12.66	-2.98	-3.31	-0.60	-0.72	-11.71	-11.70	-2.88	-12.14	-3.09	-15.91	-15.94	-17.02	-15.35	-9.67	-15.68
VCTK common	female	-6.86	-6.49	-7.55	-1.40	-1.24	-0.25	-0.24	-7.10	-6.80	-1.85	-6.25	-2.06	-7.58	-7.68	-8.86	-6.06	-4.57	-8.29
	male	-9.91	-7.22	-10.42	-0.81	-0.72	-0.20	-0.60	-10.19	-10.18	-1.41	-9.42	-1.41	-14.23	-14.85	-16.34	-13.10	-7.52	-14.91

De-identification (DeID)																			
Data	Gender	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	98.7	99.6	99.6	55.4	58.0	54.0	97.7	99.9	99.8	49.1	99.3	43.3	97.0	96.9	96.9	97.7	93.9	96.7
	male	100.0	100.0	100.0	41.2	47.0	32.6	99.0	100.0	100.0	53.1	100.0	52.6	99.2	99.3	99.4	100.0	92.7	99.3
VCTK different	female	98.8	99.5	99.6	93.3	92.3	62.6	97.8	99.9	99.9	81.8	99.3	83.1	98.0	98.1	98.7	98.6	96.1	98.1
	male	100.0	100.0	100.0	71.2	72.5	79.2	99.2	100.0	100.0	73.4	100.0	74.5	99.8	99.8	99.8	99.8	97.9	99.8
VCTK common	female	98.8	99.8	99.5	84.1	83.6	50.4	97.6	99.2	99.4	70.9	98.9	70.8	96.5	96.9	98.0	98.1	92.9	96.5
	male	99.9	100.0	99.9	43.9	42.6	62.2	93.4	99.1	99.2	60.1	99.9	62.0	99.4	99.3	97.5	99.2	92.3	97.3

Table 9: Objective results: Gain of voice distinctiveness ( $G_{VD}$ ) and De-identification (DeID) on the test data.

Gain of voice distinctiveness ( $G_{VD}$ )																			
Data	Gender	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	-6.21	-8.43	-10.07	-0.84	-0.93	-0.38	-0.10	-9.16	-8.32	-1.81	-5.93	-1.31	-12.17	-12.33	-12.21	-5.72	-5.27	-11.36
	male	-8.16	-5.98	-8.98	-0.90	-0.98	-0.26	-0.37	-7.25	-7.03	-2.42	-8.52	-2.55	-12.04	-11.95	-14.99	-11.54	-9.48	-14.71
VCTK different	female	-10.58	-9.87	-10.28	-4.11	-4.16	-1.51	0.25	-8.55	-8.78	-3.89	-9.26	-4.01	-11.67	-11.77	-13.25	-10.33	-8.35	-12.76
	male	-10.53	-5.83	-11.73	-2.61	-2.71	-1.29	-0.93	-10.21	-10.22	-2.10	-11.03	-2.47	-15.79	-15.81	-17.18	-15.56	-9.07	-16.24
VCTK common	female	-7.90	-8.20	-9.30	-1.80	-1.55	-0.56	-0.02	-8.43	-7.72	-2.57	-8.12	-2.75	-10.68	-10.69	-12.15	-10.03	-7.26	-11.56
	male	-8.04	-4.80	-10.49	-0.97	-0.92	-0.37	-0.80	-8.03	-8.03	-0.92	-9.35	-1.15	-13.77	-13.79	-16.76	-13.65	-7.12	-15.24

De-identification (DeID)																			
Data	Gender	A1	A2	B1	B2	D1	I1	K2	M1	M1c1	M1c2	M1c3	M1c4	O1	O1c1	S2	S1	S1c1	S2c1
LibriSpeech	female	99.5	98.5	97.9	41.9	40.5	39.3	91.5	99.0	99.1	55.8	96.6	52.8	94.7	95.0	98.8	96.5	92.5	99.0
	male	100.0	100.0	100.0	43.0	44.2	39.2	93.2	100.0	100.0	58.9	100.0	60.3	98.9	99.2	99.4	99.9	94.7	99.4
VCTK different	female	100.0	100.0	99.9	87.9	86.9	80.1	100.0	100.0	100.0	80.1	99.8	81.6	98.2	98.1	99.7	99.3	98.1	99.6
	male	100.0	100.0	100.0	75.0	76.5	77.7	100.0	100.0	100.0	76.2	100.0	76.7	100.0	100.0	100.0	100.0	98.7	100.0
VCTK common	female	99.6	99.3	99.3	74.6	73.7	62.6	99.9	99.7	99.7	64.5	99.5	67.3	96.0	96.9	99.4	98.2	94.8	99.3
	male	100.0	100.0	100.0	58.7	64.0	63.8	99.5	100.0	100.0	53.3	100.0	52.7	99.6	99.8	99.3	99.7	94.8	99.1

### 3.6. Using anonymized speech data for ASV training

Using anonymized speech data for ASV training leads to a stronger attack model referred to as *semi-informed* ( $ASV_{eval}^{anon}$ ). The resulting privacy protection is assessed in Tables 10, 11 in terms of EER,  $C_{llr}$ , and  $C_{llr}^{min}$ , in Tables 12, 13 in terms of the two ZEBRA metrics, and in Tables 14, Table 15 in terms of linkability.

Table 10: Objective results: EER,  $C_{lr}$ , and  $C_{lr}^{\min}$  for the semi-informed attack model on the development data.

EER – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	8.66	18.89	10.94	23.44	23.30	18.18	3.27
	male	1.24	7.45	1.09	14.60	24.22	11.18	1.55
VCTK different	female	2.86	12.41	3.54	14.94	14.94	13.03	1.91
	male	1.44	10.92	3.47	19.45	26.35	10.82	6.05
VCTK common	female	2.62	14.53	4.07	14.83	18.60	12.21	1.45
	male	1.43	16.81	3.13	22.51	32.19	13.68	3.13

$C_{lr}$ – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	42.9	6.9	46.2	2.6	4.0	4.4	1.5
	male	14.2	3.6	16.3	1.5	6.2	2.0	0.7
VCTK different	female	1.1	2.1	0.8	3.2	8.4	2.4	1.4
	male	1.2	2.2	1.1	3.0	16.0	3.3	2.2
VCTK common	female	0.9	1.6	1.4	1.9	6.6	1.2	0.5
	male	1.6	2.8	1.4	2.1	12.4	1.7	1.7

$C_{lr}^{\min}$ – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.304	0.563	0.351	0.666	0.627	0.566	0.114
	male	0.034	0.241	0.035	0.464	0.658	0.365	0.063
VCTK different	female	0.100	0.403	0.122	0.475	0.487	0.440	0.076
	male	0.052	0.373	0.127	0.602	0.764	0.376	0.223
VCTK common	female	0.088	0.473	0.143	0.484	0.532	0.373	0.043
	male	0.050	0.518	0.103	0.627	0.825	0.427	0.130

Table 11: Objective results: EER,  $C_{lr}$ , and  $C_{lr}^{\min}$  for the semi-informed attack model on the test data.

EER – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	7.66	12.23	8.03	26.28	18.25	12.23	0.36
	male	1.11	10.69	1.56	16.48	23.39	11.14	3.79
VCTK different	female	4.89	16.20	9.05	20.37	22.22	17.70	1.59
	male	2.07	10.91	4.13	19.23	24.80	14.29	5.11
VCTK common	female	2.89	18.79	6.36	21.68	19.94	16.18	1.73
	male	1.13	13.28	2.54	16.67	27.12	13.28	3.11

$C_{lr}$ – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	26.8	3.0	30.4	3.7	3.3	2.5	0.1
	male	15.3	5.1	14.9	1.4	7.9	1.9	1.7
VCTK different	female	1.5	3.6	2.8	5.7	10.4	4.3	1.1
	male	1.8	2.2	1.9	5.4	15.3	4.2	2.7
VCTK common	female	0.9	2.0	1.4	3.6	7.8	2.3	0.6
	male	1.0	1.9	1.2	3.0	10.6	1.8	1.4

$C_{lr}^{\min}$ – Semi-informed (aa)								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.183	0.384	0.204	0.726	0.548	0.384	0.011
	male	0.041	0.329	0.045	0.523	0.699	0.348	0.115
VCTK different	female	0.169	0.528	0.308	0.624	0.675	0.561	0.057
	male	0.072	0.368	0.147	0.597	0.722	0.453	0.199
VCTK common	female	0.091	0.552	0.211	0.614	0.608	0.496	0.066
	male	0.036	0.413	0.072	0.534	0.764	0.411	0.116

Table 12: Objective results: ZEBRA expected and worst-case privacy disclosure for the semi-informed attack model on the development data.

ZEBRA: Expected privacy disclosure (population) – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.492	0.307	0.458	0.232	0.261	0.303	0.632
	male	0.696	0.541	0.694	0.376	0.239	0.449	0.671
VCTK different	female	0.646	0.421	0.630	0.368	0.359	0.392	0.663
	male	0.682	0.442	0.625	0.276	0.161	0.440	0.551
VCTK common	female	0.653	0.368	0.612	0.361	0.328	0.445	0.690
	male	0.683	0.337	0.644	0.261	0.120	0.404	0.620

ZEBRA: worst-case privacy disclosure (individual) – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	3.829	2.884	3.801	2.884	2.949	3.015	2.829
	male	4.055	3.298	4.073	2.932	2.641	3.156	3.091
VCTK different	female	3.972	3.001	3.980	2.386	2.892	2.462	3.650
	male	4.037	2.632	3.910	2.110	1.985	2.850	3.208
VCTK common	female	3.596	2.690	3.513	2.401	2.271	2.286	3.660
	male	3.616	2.001	3.355	2.100	1.447	2.231	2.496

Table 13: Objective results: ZEBRA expected and worst-case privacy disclosure for the semi-informed attack model on the test data.

ZEBRA: Expected privacy disclosure (population) – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.584	0.436	0.568	0.189	0.317	0.437	0.713
	male	0.690	0.477	0.687	0.333	0.207	0.461	0.630
VCTK different	female	0.594	0.329	0.491	0.260	0.223	0.305	0.678
	male	0.667	0.446	0.611	0.280	0.191	0.385	0.568
VCTK common	female	0.653	0.314	0.563	0.269	0.272	0.353	0.669
	male	0.694	0.414	0.668	0.324	0.163	0.416	0.631

ZEBRA: worst-case privacy disclosure (individual) – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	3.979	3.235	3.966	2.690	3.074	3.155	3.967
	male	3.924	3.031	3.873	2.403	2.278	2.786	2.636
VCTK different	female	3.655	2.490	3.183	2.258	2.070	2.429	3.894
	female	3.921	2.589	3.844	2.296	1.743	3.137	3.113
VCTK common	female	3.557	2.350	2.924	1.718	1.748	1.804	2.748
	male	3.675	2.206	3.630	1.822	1.578	2.292	2.931

Table 14: Objective results: Linkability for the semi-informed attack model on the development data.

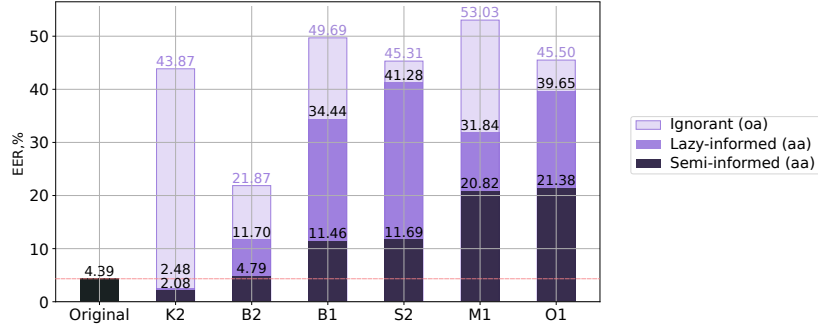
Linkability – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.801	0.563	0.764	0.484	0.483	0.578	0.921
	male	0.974	0.814	0.977	0.652	0.455	0.725	0.956
VCTK different	female	0.931	0.700	0.915	0.645	0.650	0.677	0.952
	female	0.968	0.726	0.915	0.523	0.375	0.715	0.836
VCTK common	female	0.935	0.629	0.900	0.634	0.565	0.687	0.951
	male	0.963	0.589	0.914	0.460	0.289	0.644	0.910

Table 15: Objective results: Linkability for the semi-informed attack model on the test data.

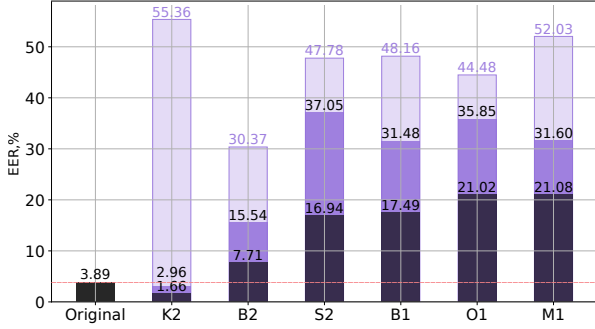
Linkability – Semi-informed								
Data	Gender	Orig	B1	B2	O1	M1	S2	K2
LibriSpeech	female	0.898	0.700	0.891	0.408	0.577	0.710	0.988
	male	0.958	0.689	0.964	0.606	0.448	0.743	0.915
VCTK different	female	0.881	0.609	0.773	0.512	0.480	0.574	0.960
	female	0.950	0.727	0.901	0.531	0.407	0.650	0.865
VCTK common	female	0.924	0.540	0.834	0.475	0.491	0.602	0.955
	male	0.972	0.659	0.933	0.583	0.347	0.663	0.909

Figure 15 shows EER results for the semi-informed (darker, lower bars), lazy-informed, and ignorant attack models on (a) *LibriSpeech-test* and (b) *VCTK-test*. For two test sets (*LibriSpeech-test* and *VCTK-test (different)*), system **K2** even delivers lower EERs for the semi-informed attack model than for original data without anonymization. For the semi-informed attack model, x-vector based anonymization techniques related to **B1** (**O1**, **M1**, **S2**) demonstrate higher EER than other considered approaches (**B2**, **K2**). The best results against the semi-informed attack model are obtained by systems **M1** and **O1**.

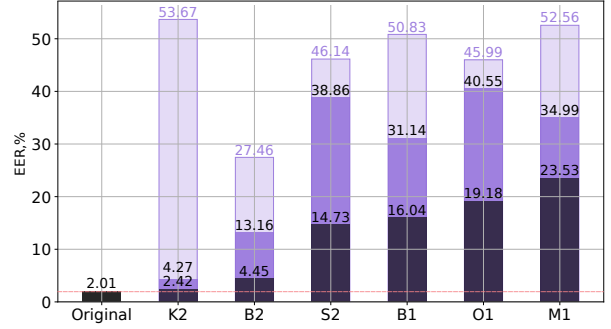
Figure 16 shows mean EER results (over all VoicePrivacy development and test datasets) separately for male and female speakers. Speaker anonymization performs differently for male and female speakers. For system **M1**, anonymization for male speakers works better than for female speakers for all attack models, and for **B2**, on the contrary, results for female speakers are better.



(a) LibriSpeech-test



(b) VCTK-test (different)



(c) VCTK-test (common)

Figure 15: EER results achieved by different anonymization systems on the test datasets against the three attack models, compared to the EER achieved on the original data.

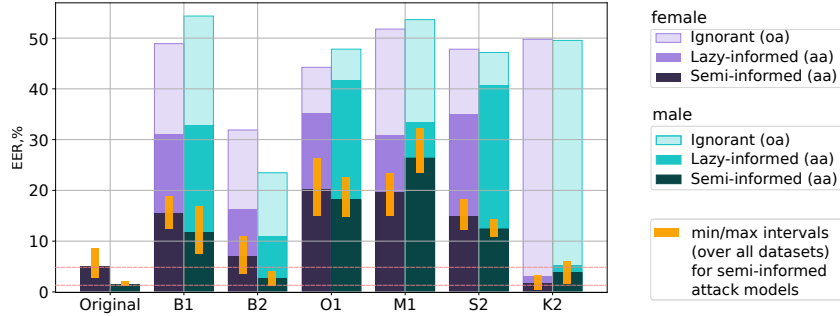


Figure 16: Mean EER results achieved by different anonymization systems over all development and test datasets for female and male speakers against the three attack models, compared to the EER achieved on the original data.

### 3.7. Comparison of privacy metrics

The considered privacy metrics correlate with each other to a variable extent. In this section, we investigate this observation in more detail. Figure 17 presents EER vs.  $C_{llr}^{\min}$  results for ignorant, lazy-informed, and semi-informed attack models for different datasets and anonymization systems, as well as for original (non-anonymized) data. Similarly, Figure 18 demonstrates the relation between linkability and  $C_{llr}^{\min}$  metrics. We observe a consistent correlation between all three metrics, especially for the lazy-informed and semi-informed attack models.

Figure 19 shows scatterplots for  $(EER, C_{llr})$  for the three attack models. For the ignorant attack model (Figure 19a), the results for signal-processing methods (**B2, D1, I1**) and x-vector based methods form two separate clusters.

Figure 20 demonstrates the relation between linkability and EER. Both metrics perform similarly in most cases for lazy-informed and semi-informed attackers, though for the ignorant attacker they behave differently in some particular cases, e.g., for system **K2**. There are cases where the EER is above 50% that can be considered as perfect privacy, while linkability for these cases is higher than 0 meaning that according to linkability there is still some exploitable information for attackers left in the scores.

ZEBRA expected privacy disclosure (population) and  $C_{llr}^{\min}$  have a linear dependency as shown in Figure 21. ZEBRA worst case privacy disclosure (individual) differs from all the considered metrics as shown in Figure 22.

Finally, Figure 23 shows the relation between De-identification (DeID) on the one hand and Gain of voice distinctiveness ( $G_{VD}$ ), EER, or  $C_{llr}^{\min}$  on the other hand. In particular, Figure 23a shows that methods derived from **B1** provide near-to-perfect de-identification, while the signal-processing anonymization solutions better preserve voice distinctiveness, and **K2** is the only system which reaches a good trade-off between de-identification performance and voice distinctiveness.

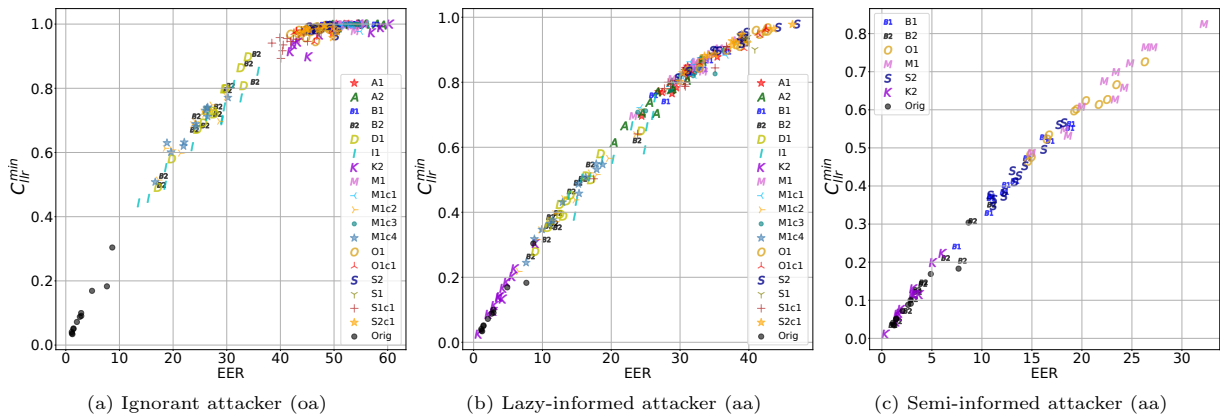


Figure 17: EER vs.  $C_{llr}^{\min}$  results for the three attack models. Each point in the figure represents results on a dataset from the set of all 12 VoicePrivacy development and test datasets. Higher EER and  $C_{llr}^{\min}$  values correspond to better privacy.

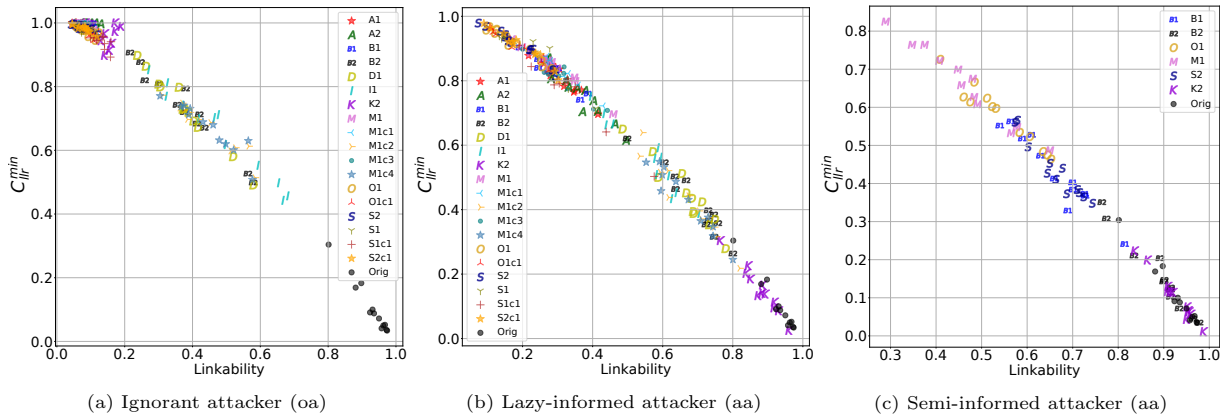


Figure 18: Linkability vs.  $C_{llr}^{\min}$  results for the three attack models. Each point in the figure represents results on a dataset from the set of all 12 VoicePrivacy development and test datasets. Higher  $C_{llr}^{\min}$  and smaller *linkability* values correspond to better privacy.



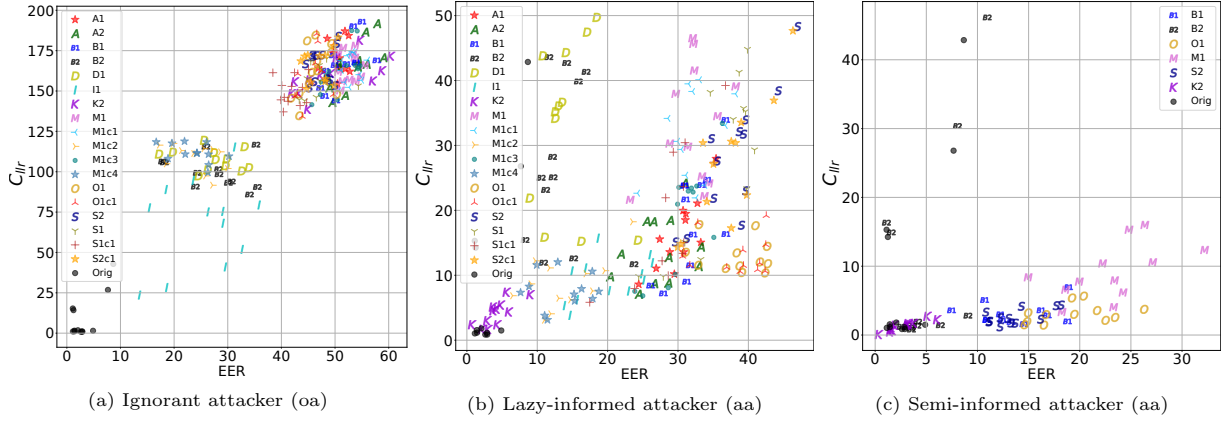


Figure 19: EER vs.  $C_{IIr}$  results for the three attack models. Each point in the figure represents results on a particular dataset from the set of all 12 VoicePrivacy development and test datasets.

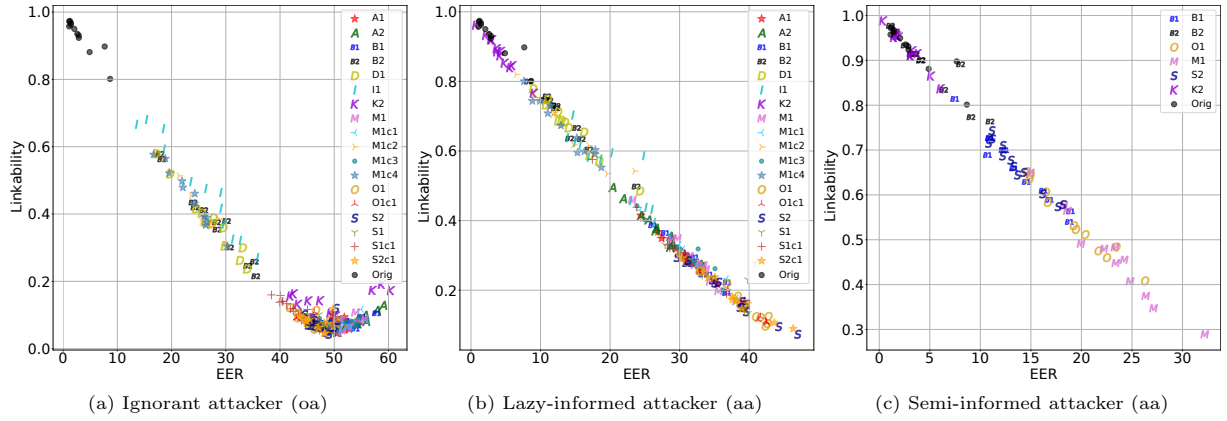


Figure 20: EER vs. Linkability results for the three attack models. Each point in the figure represents results on a particular dataset from the set of all 12 VoicePrivacy development and test datasets.

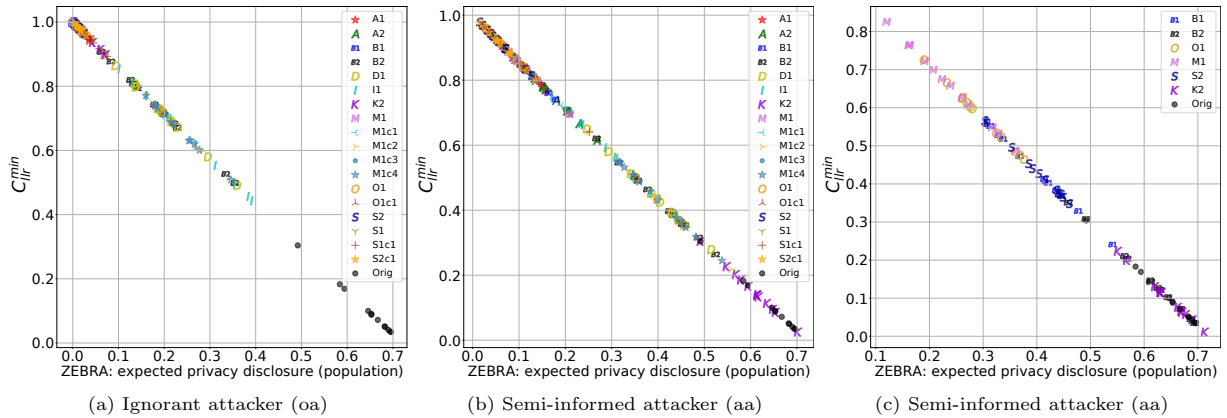


Figure 21: Expected privacy disclosure (population) vs.  $C_{IIr}^{\min}$  results for the three attack models. Each point in the figure represents results on a particular dataset from the set of all 12 VoicePrivacy development and test datasets. Higher  $C_{IIr}^{\min}$  and lower expected privacy disclosure metric values correspond to better privacy.

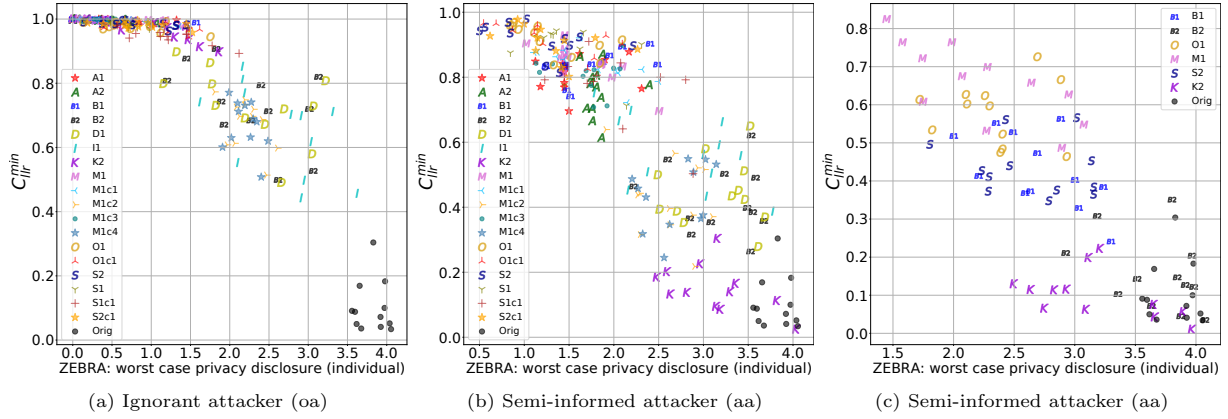


Figure 22: Worst case privacy disclosure (individual) vs.  $C_{llr}^{\min}$  results for the three attack models. Each point in the figure represents results on a particular dataset from the set of all 12 VoicePrivacy development and test datasets. Smaller worst case privacy disclosure metric values and higher  $C_{llr}^{\min}$  values correspond to better privacy.

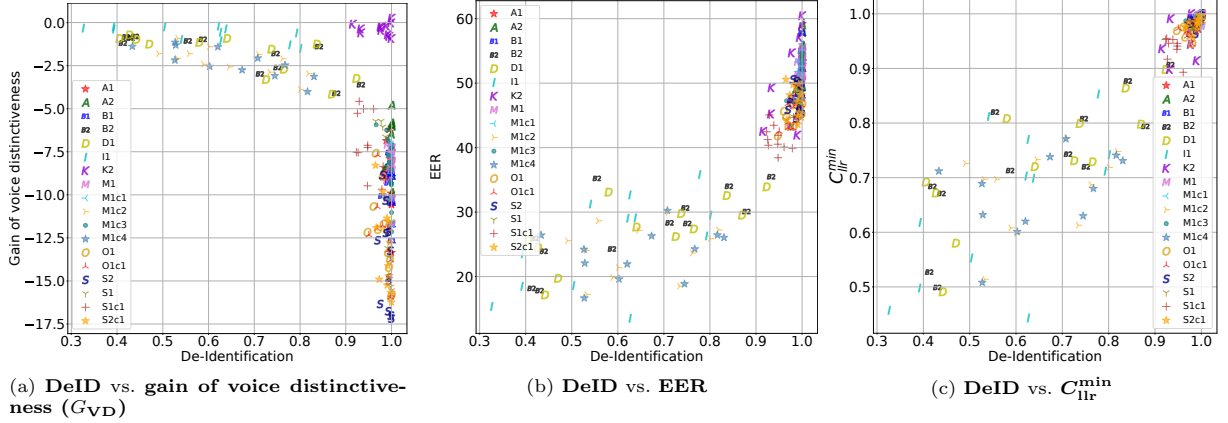


Figure 23: De-identification (DeID) vs. other metrics. Each point in the figure represents results on a particular dataset from the set of all 12 VoicePrivacy development and test datasets. In (b) and (c), the ignorant attack model is used to compute EER and  $C_{llr}^{\min}$ . Higher DeID corresponds to better privacy.

## 4. Subjective evaluation

This section presents subjective evaluation results for speaker verifiability, speech naturalness, and speech intelligibility.

### 4.1. Subjective evaluation on verifiability, naturalness, and intelligibility

These three metrics were evaluated via a unified subjective evaluation test. The input speech trial can be an original or anonymized test set trial from the same or a different speaker. For intelligibility of the input trial, the evaluators assigned a score from 1 (‘totally unintelligible’) to 10 (‘totally intelligible’). For naturalness, the evaluators assigned a score from 1 (‘totally unnatural’) to 10 (‘totally natural’). For speaker verifiability, the evaluators were required to listen to one original enrollment utterance of the same or different speaker and rate the similarity between the input trial and the enrollment voice using a scale of 1 to 10, where 1 denotes ‘different speakers’ and 10 denotes ‘the same speaker’ with highest confidence. The evaluators were instructed to assign the scores through a role-playing game.

### *Instructions for role-playing*

When an evaluator started an evaluation session, the following instruction was displayed:<sup>7</sup>

“  
Please imagine that you are working at a TV or radio company. You wish to broadcast interviews of person X, but this person X does not want to disclose his/her identity. Therefore you need to modify speech signals in order to hide it. You have several automated tools to change speaker identity. Some of them hide the identity well, but severely degrade audio quality. Some of them hide the identity, but the resulting speech sounds very unnatural and may become less intelligible. In such cases, the privacy of person X is protected, but you will receive many complaints from the audience and listeners of TV/radio programs. You need to balance privacy of person X and satisfaction of TV/radio program audience and listeners. Your task is to evaluate such automated tools to change speaker identity and find out well-balanced tools.  
”

Each of the three subjective metrics had a detailed instruction. The evaluator was asked to imagine the scene when evaluating the corresponding metric.

“  
**Subjective speech naturalness**  
You will listen to either original audio and audio modified by the above anonymization tools. Some of them result in artifacts and degradation due to poor audio processing.  
Now, please listen to audio A and answer how much you can hear the audio degradation. Please judge based on the characteristics of the audio rather than what is being said.  
You need to select a score between 1 and 10, where a higher score indicates less degradation. In particular, 1 means “audio A exhibits severe audio degradation” and 10 means “audio A does not exhibit any degradation”. Please note that the original audio includes background noise.  
”

“  
**Subjective speaker verifiability (similarity)**  
Your next task is to compare the processed or unprocessed audio A with audio B where the original person may speak different sentences. From the voices, you must determine whether they are from the same person or another person. Now, please listen to audio A above and audio B below, and determine if they were uttered by the same speaker. Please judge based on the characteristics of the voice rather than what is being said.  
You need to select one score between 1 and 10, where a higher score denotes higher speaker similarity. In particular, 1 means “audio A and B were uttered by different speakers for sure” and 10 means “audio A and B were uttered by the same speaker for sure.”  
”

---

<sup>7</sup>The bank call center scenario mentioned in the evaluation plan was eventually replaced by this one.

“  
**Subjective speech intelligibility**  
 For the final task, you are required to listen to audio A again and try to understand the audio content. Please judge how understandable audio A is. You need to select one score between 1 and 10, where a higher score denotes higher intelligibility. In particular, 1 means “audio A is NOT understandable at all” and 10 means “audio A is perfectly understandable.”  
 ”

#### 4.2. Score distribution in violin plot

To reduce the perceptual bias of each individual evaluator, the naturalness, intelligibility, and verifiability scores collected via the unified subjective test were processed using normalized-rank normalization (Rosenberg & Ramabhadran, 2017). The processed scores are float numbers varying from 0 to 1. The Mann-Whitney-U test was further used for statistical significance tests (Rosenberg & Ramabhadran, 2017).

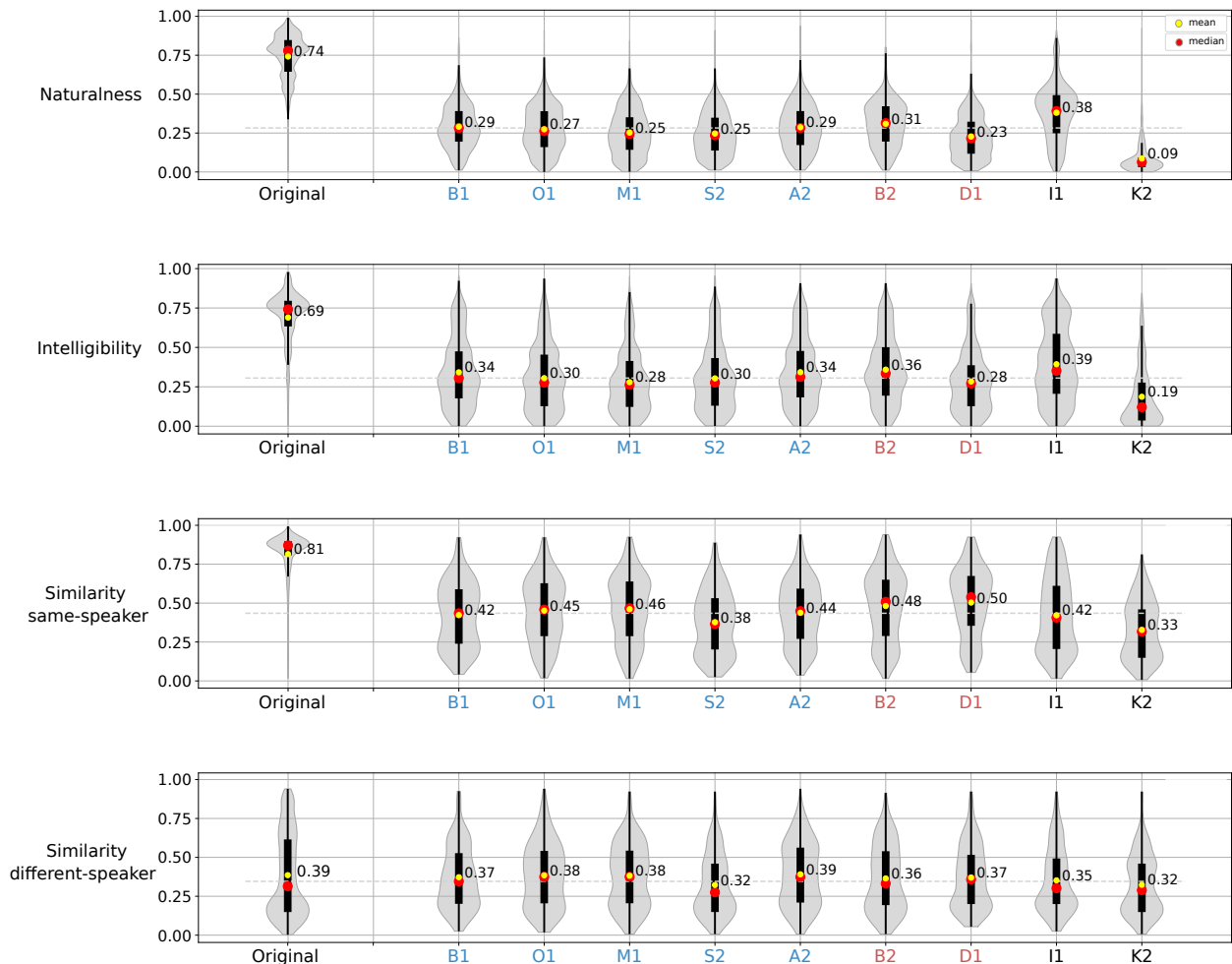


Figure 24: Violin plots of normalized **subjective speech naturalness**, **intelligibility**, and **speaker similarity** scores pooled over *LibriSpeech-test* and *VCTK-test*. The dotted line indicates the median for **B1**. Numbers indicate mean values. Higher naturalness and intelligibility scores correspond to better utility, and lower similarity scores to better privacy.

The distributions of normalized naturalness, intelligibility, and speaker similarity scores obtained from the unified subjective test are displayed in Figure 24 as violin plots (Hintze & Nelson, 1998). The similarity scores for same-speaker and different-speaker pairs are plotted separately, since they are expected to be different.

The significance test evaluates whether the differences between the scores of two systems are statistically significant. We followed Rosenberg & Ramabhadran (2017) and used the two-sided Mann-Whitney test. The results are shown in Tables 16 and 17. As the first row of Table 16a demonstrates, the scores of anonymized same-speaker data from all the systems are statistically different from those of the original same-speaker data. From the first two rows of Tables 17b and 17a, the results indicate that the scores of anonymized data from all the systems are statistically different from those of the original data.

Table 16: Significance test on subjective speaker similarity results pooled over *LibriSpeech-test*, *VCTK-test (common)*, and *VCTK-test (different)*. Cells in blue color denotes statistical significance ( $p \ll 0.01$ ), while gray color denotes insignificant difference ( $p > 0.01$ ). Blue and red colors in the system notations indicate systems developed from B1 and B2, respectively. Tar and Scores of anonymized target and non-target speakers data were separated, and the results are listed in (a) and (b) below, respectively.

(a) Same-speaker

	Original	B1	O1	M1	S2	A2	B2	D1	I1	K2
Original		$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
B1	$\ll 0.01$		0.027	0.0057	0.0007	0.258	$\ll 0.01$	$\ll 0.01$	0.660	$\ll 0.01$
O1	$\ll 0.01$	0.027		0.483	$\ll 0.01$	0.266	0.042	0.0002	0.018	$\ll 0.01$
M1	$\ll 0.01$	0.0057	0.483		$\ll 0.01$	0.077	0.167	0.0030	0.0047	$\ll 0.01$
S2	$\ll 0.01$	0.0007	$\ll 0.01$	$\ll 0.01$		$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.0087	0.0004
A2	$\ll 0.01$	0.258	0.266	0.077	$\ll 0.01$		0.0020	$\ll 0.01$	0.135	$\ll 0.01$
B2	$\ll 0.01$	$\ll 0.01$	0.042	0.167	$\ll 0.01$	0.0020		0.140	0.0001	$\ll 0.01$
D1	$\ll 0.01$	$\ll 0.01$	0.0002	0.0030	$\ll 0.01$	$\ll 0.01$	0.140		$\ll 0.01$	$\ll 0.01$
I1	$\ll 0.01$	0.660	0.018	0.0047	0.0087	0.135	0.0001	$\ll 0.01$		$\ll 0.01$
K2	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.0004	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	

(b) Different-speaker

	Original	B1	O1	M1	S2	A2	B2	D1	I1	K2
Original		0.440	0.171	0.241	0.0004	0.038	0.653	0.634	0.411	0.0005
B1	0.440		0.327	0.379	0.0002	0.119	0.490	0.839	0.102	0.0003
O1	0.171	0.327		0.943	$\ll 0.01$	0.546	0.122	0.267	0.012	$\ll 0.01$
M1	0.241	0.379	0.943		$\ll 0.01$	0.478	0.167	0.293	0.018	$\ll 0.01$
S2	0.0004	0.0002	$\ll 0.01$	$\ll 0.01$		$\ll 0.01$	0.0047	0.0004	0.033	0.977
A2	0.038	0.119	0.546	0.478	$\ll 0.01$		0.036	0.078	0.0016	$\ll 0.01$
B2	0.653	0.490	0.122	0.167	0.0047	0.036		0.603	0.467	0.0066
D1	0.634	0.839	0.267	0.293	0.0004	0.078	0.603		0.187	0.0006
I1	0.411	0.102	0.012	0.018	0.033	0.0016	0.467	0.187		0.038
K2	0.0005	0.0003	$\ll 0.01$	$\ll 0.01$	0.977	$\ll 0.01$	0.0066	0.0006	0.038	

Table 17: Significance test on subjective naturalness and intelligibility results pooled over *LibriSpeech-test*, *VCTK-test (common)*, and *VCTK-test (different)*. Cells in blue color denotes statistical significance ( $p \ll 0.01$ ), while gray color denotes ( $p > 0.01$ ). Blue and red colors in the system notations indicate systems developed from B1 and B2, respectively. Scores of both anonymized target and non-target data were merged for each system.

(a) Naturalness

	Original	B1	O1	M1	S2	A2	B2	D1	I1	K2
Original		$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
B1	$\ll 0.01$		0.017	$\ll 0.01$	$\ll 0.01$	0.562	0.0027	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
O1	$\ll 0.01$	0.017		0.0019	$\ll 0.01$	0.081	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
M1	$\ll 0.01$	$\ll 0.01$	0.0019		0.398	$\ll 0.01$	$\ll 0.01$	0.0003	$\ll 0.01$	$\ll 0.01$
S2	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.398		$\ll 0.01$	$\ll 0.01$	0.0026	$\ll 0.01$	$\ll 0.01$
A2	$\ll 0.01$	0.562	0.081	$\ll 0.01$	$\ll 0.01$		0.0006	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
B2	$\ll 0.01$	0.0027	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.0006		$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
D1	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.0003	0.0026	$\ll 0.01$	$\ll 0.01$		$\ll 0.01$	$\ll 0.01$
I1	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$		$\ll 0.01$
K2	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	

(b) Intelligibility

	Original	B1	O1	M1	S2	A2	B2	D1	I1	K2
Original		$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
B1	$\ll 0.01$		0.0003	$\ll 0.01$	$\ll 0.01$	0.866	0.043	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
O1	$\ll 0.01$	0.0003		0.0053	0.764	0.0001	$\ll 0.01$	0.048	$\ll 0.01$	$\ll 0.01$
M1	$\ll 0.01$	$\ll 0.01$	0.0053		0.013	$\ll 0.01$	$\ll 0.01$	0.421	$\ll 0.01$	$\ll 0.01$
S2	$\ll 0.01$	$\ll 0.01$	0.764	0.013		$\ll 0.01$	$\ll 0.01$	0.101	$\ll 0.01$	$\ll 0.01$
A2	$\ll 0.01$	0.866	0.0001	$\ll 0.01$	$\ll 0.01$		0.064	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
B2	$\ll 0.01$	0.043	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.064		$\ll 0.01$	0.0059	$\ll 0.01$
D1	$\ll 0.01$	$\ll 0.01$	0.048	0.421	0.101	$\ll 0.01$	$\ll 0.01$		$\ll 0.01$	$\ll 0.01$
I1	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	0.0059	$\ll 0.01$		$\ll 0.01$
K2	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$	

#### 4.3. DET curves

To investigate the difference across systems, we plot detection error trade-off (DET) curves (Martin et al., 1997). These curves assume a detection task, where the decision for a given trial is made by comparing the score with a threshold. The false alarm and miss rates are computed as a function of the threshold and plotted against each other. For naturalness and intelligibility the task is to detect original data, while for speaker similarity the task is to detect whether the trial utterance is from the same speaker as the enrollment utterance. The closer the DET curves are to the top-right corner of each plot, the higher the naturalness, intelligibility, and privacy preservation. Once again, the DET curves for same-speaker and different-speaker pairs are plotted separately, since they are expected to be different.

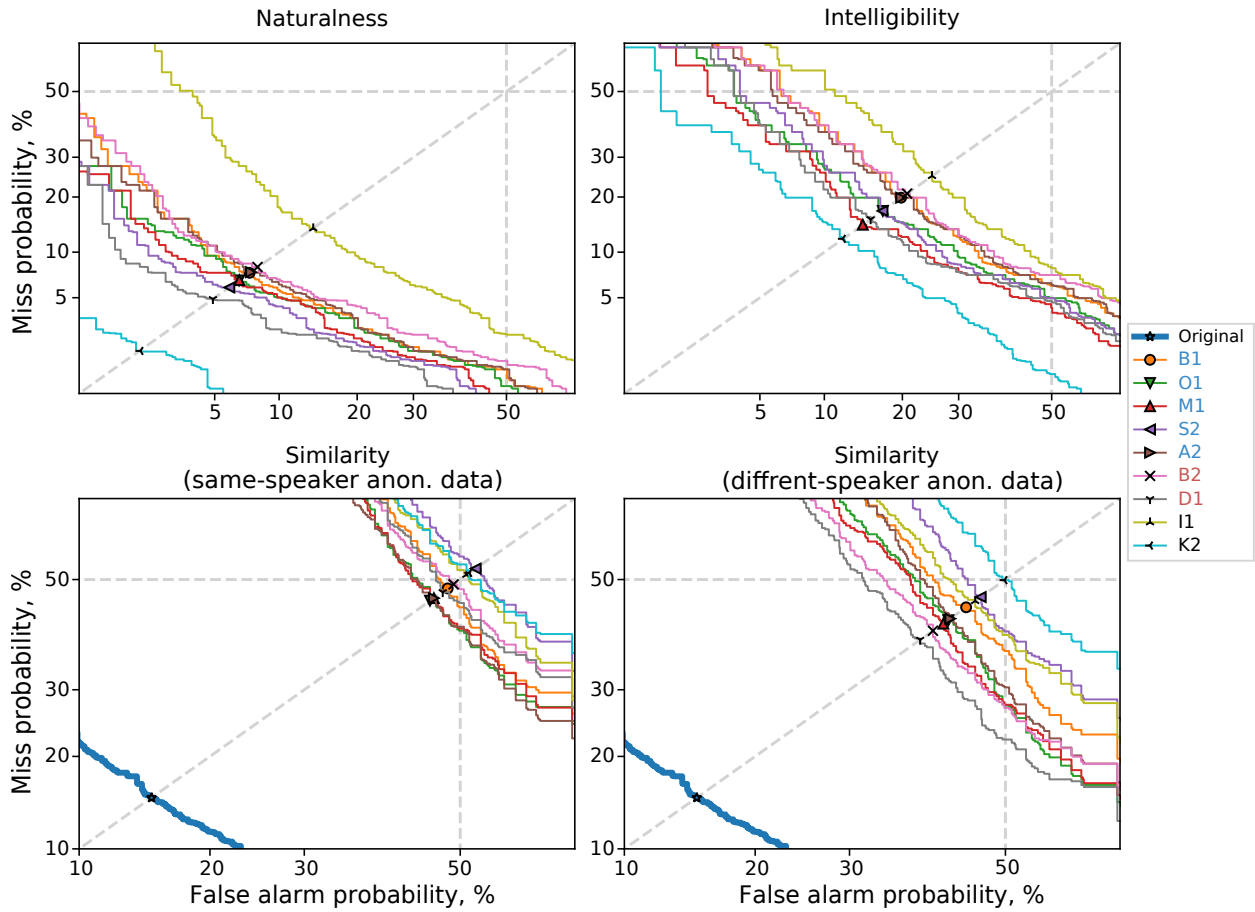


Figure 25: DET curves based on subjective evaluation scores pooled over *LibriSpeech-test* and *VCTK-test* datasets.

The four types of DET curves are plotted in Figure 25.

Concerning naturalness and intelligibility, the DET curves for anonymized data are far from the top-right corner, suggesting that anonymized data are inferior to original data in terms of naturalness and intelligibility. The naturalness DET curves of **I1** and **K2** seem to deviate from the other anonymization systems. While other systems are based on either **B1** or **B2**, **I1** uses a different signal processing based approach, and **K2** uses a different deep learning method. As such, **I1** avoids several errors such as ASR AM errors in **B1**, which may contribute to its naturalness. However, it is interesting to note how different signal processing algorithms result in different perceptual naturalness and intelligibility. Also note that none of the systems except **I1** outperforms **B2**.

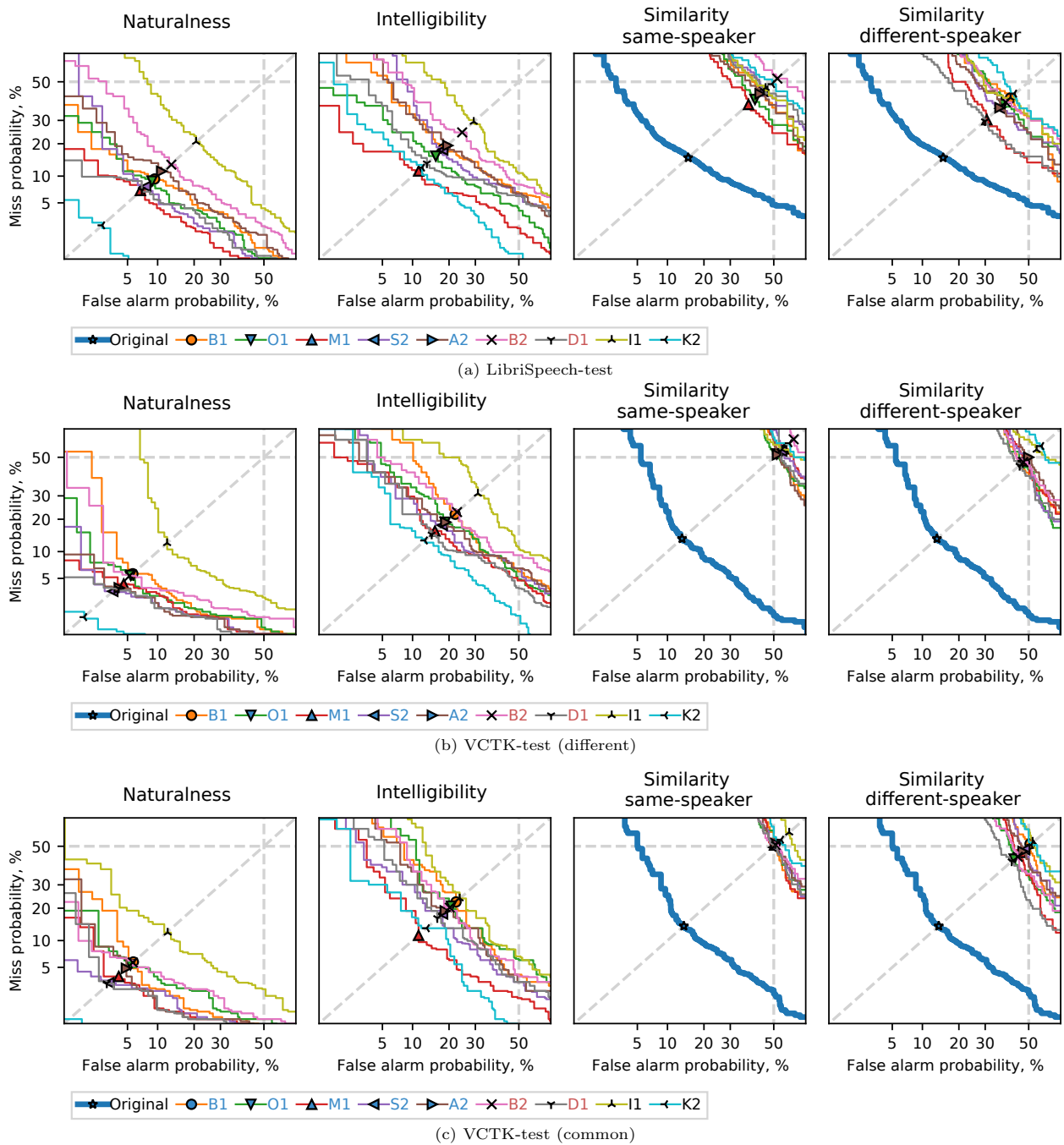


Figure 26: DET curves for each test set.

Concerning speaker similarity, both in the same-speaker and different-speaker cases, the DET curves of original data are close to the bottom-left corner while those of anonymized data are close to top-right corner. In other words, anonymization of the trial utterances makes it difficult to decide whether the original enrollment utterance comes from the same speaker or not. The similarity DET curves of **K2**, **S2**, and **I1** in the same-speaker case are closer to the top-right corner than others. However, these three systems behave



quite differently in terms of naturalness and intelligibility, with **I1** and **K2** achieving the highest and lowest median score, respectively. This implies that an anonymized trial may sound like the voice of a different speaker simply because of the severe distortion caused by anonymization. Similar results can be observed from the curves in Figure 26, which are separately plotted on the three test sets.

In summary, all the submitted anonymization systems can anonymize the perceived speaker identity to some degree. However, none of them can produce an anonymized speech that is as natural and intelligible as original speech data. One signal-processing-based anonymization method (**I1**) degrades the naturalness and intelligibility of anonymized trials less severely, but it still degrades them to some extent.

## 255 5. Comparison of objective and subjective evaluation results

In this section, we are interested in comparing objective and subjective evaluation results. From the subjective speaker verifiability (similarity) scores, we computed EER, ROCCH-EER,  $C_{\text{llr}}$ , and  $C_{\text{llr}}^{\text{min}}$ . We then compare these metrics with those obtained from objective speaker verifiability scores. The values are given in Table 18 and plotted against each other in Figures 27, 28, 29, and 30.

The marker “Original” in Figure 27 denotes original trials, and other markers denote anonymized trials from the submitted systems. The comparison between original and anonymized trials indicates that both objective and subjective EERs increase after the trial is anonymized. However, the increase varies across the anonymization systems and test sets. Similar results can be observed for ROCCH-EER,  $C_{\text{cllr}}$ , and  $C_{\text{cllr}}^{\text{min}}$ . Furthermore, the objective and subjective EERs are positively correlated (Figures 28, 29 and 30). This suggests that the concerned anonymization methods can hide the speaker identity to some degree from both ASV system and human ears. This is an encouraging message from the challenge.

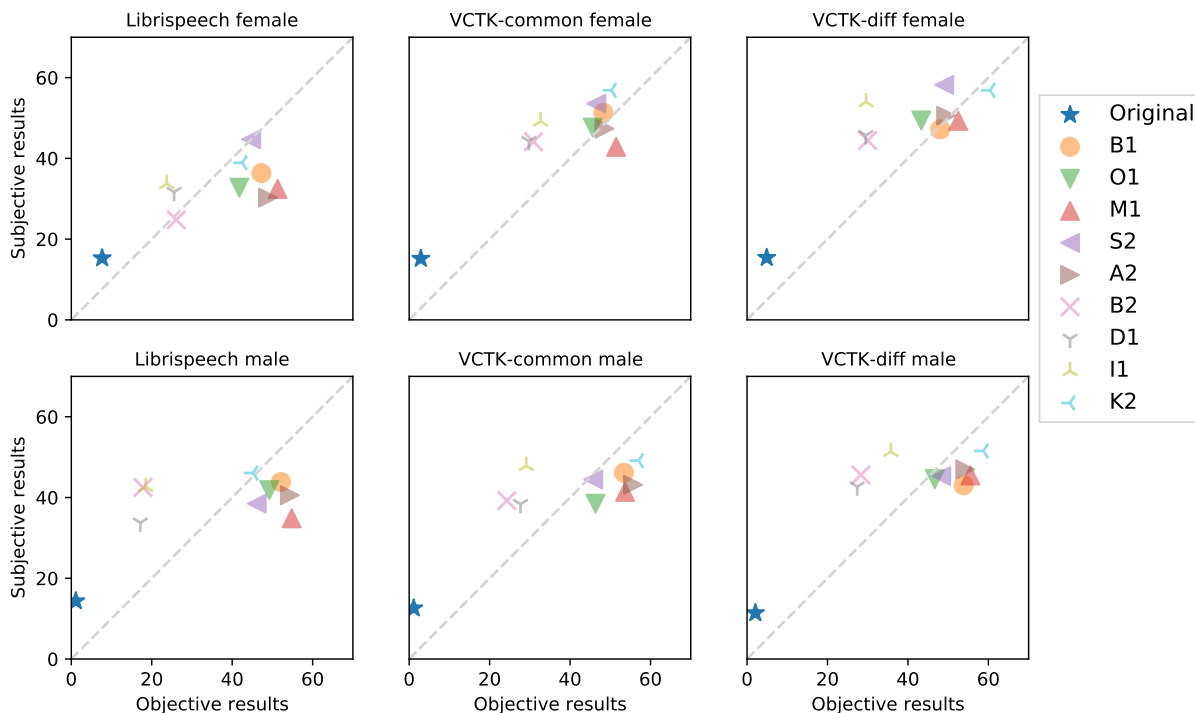


Figure 27: Objective (ignorant attack model) versus subjective EER.

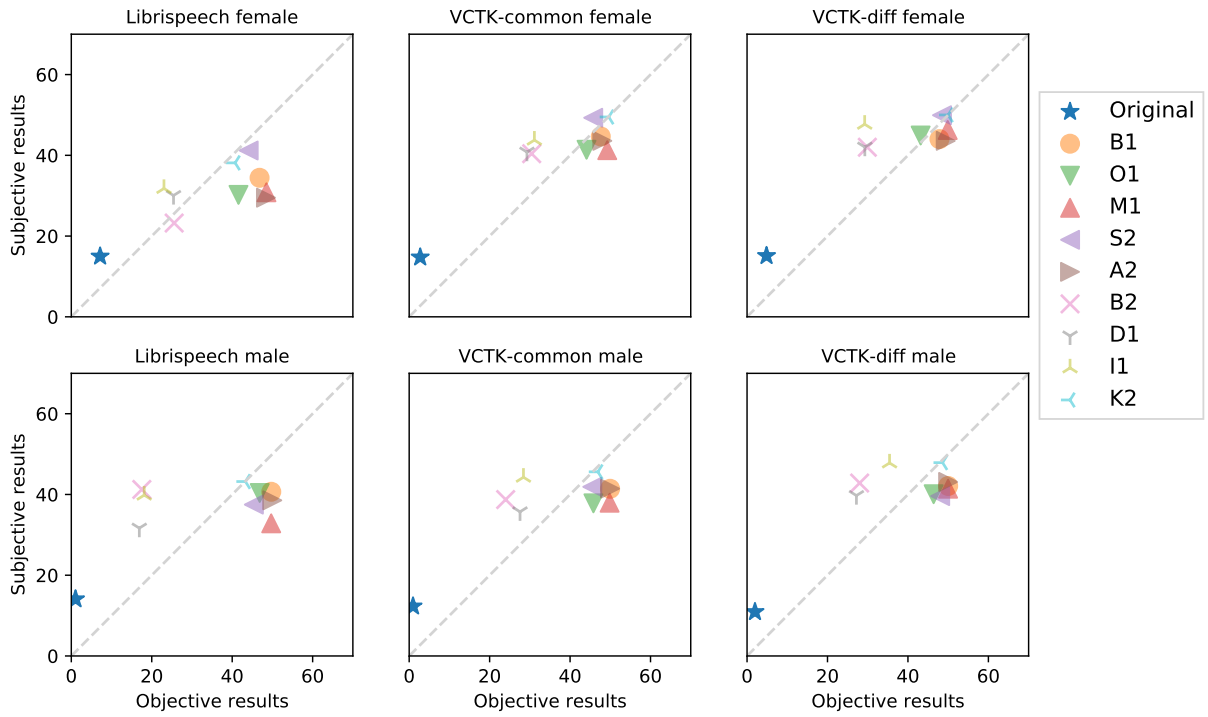


Figure 28: Objective (ignorant attack model) versus subjective ROCCH-EER.

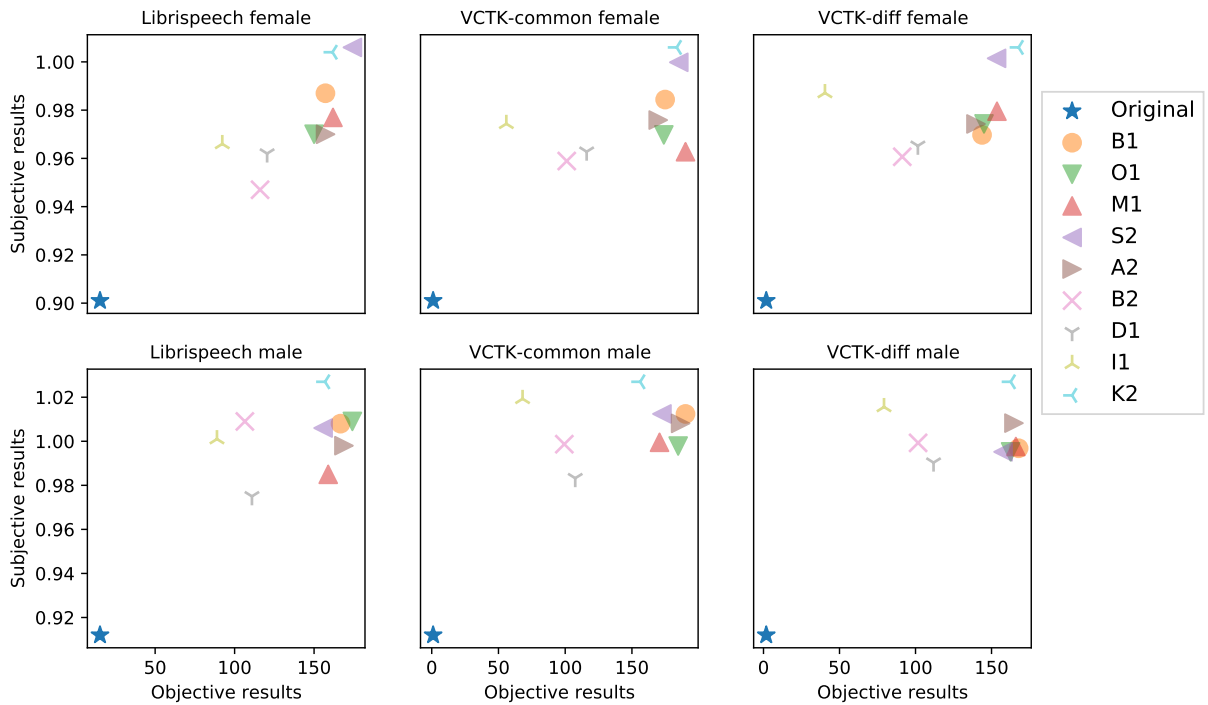


Figure 29: Objective (ignorant attack model) versus subjective  $C_{11r}$ .

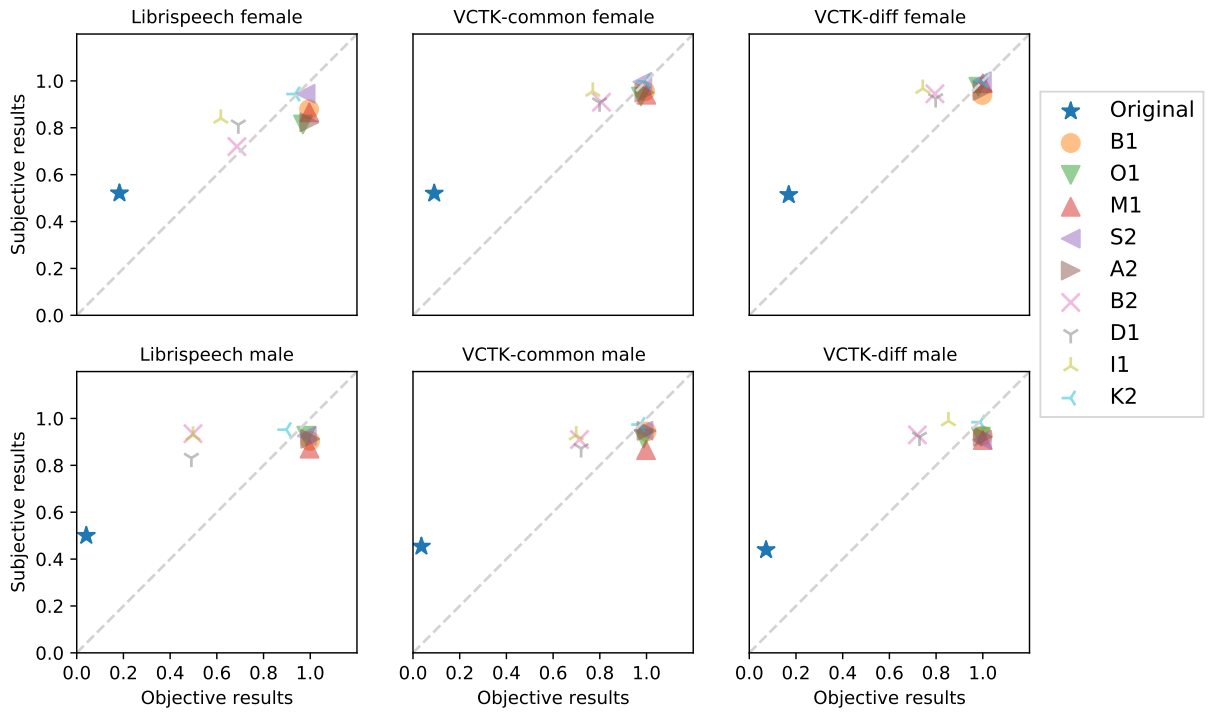


Figure 30: Objective (ignorant attack model) versus subjective  $C_{llr}^{\min}$ .

Table 18: Objective vs. subjective metrics for test sets. Objective metrics are computed for the ignorant attack model.

EER – objective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	7.664	47.260	41.790	51.280	44.710	48.910	26.090	25.550	23.720	42.520
	male	1.114	52.120	49.220	54.790	46.100	54.340	17.820	17.150	18.490	45.210
VCTK (common)	female	2.890	48.270	45.660	51.450	46.530	48.550	30.920	29.770	32.660	50.290
	male	1.130	53.390	46.330	53.670	45.760	55.650	24.290	27.680	29.100	57.060
VCTK (different)	female	4.887	48.050	43.310	52.520	49.020	49.490	29.990	29.530	29.580	60.440
	male	2.067	53.850	46.670	55.510	48.280	54.250	28.300	27.380	35.760	58.780
EER – subjective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	15.301	36.343	32.744	32.426	44.702	30.278	24.787	31.660	33.730	38.919
	male	14.348	43.837	41.823	34.847	38.484	40.568	42.494	33.739	42.636	46.064
VCTK (common)	female	15.169	51.308	47.616	42.847	53.563	47.362	44.128	44.252	49.192	56.852
	male	12.575	46.131	38.467	41.400	44.453	43.160	39.231	38.348	47.872	49.124
VCTK (different)	female	15.396	47.178	49.390	49.291	58.199	50.587	44.436	45.700	53.953	56.853
	male	11.398	43.024	44.554	45.448	45.323	46.977	45.603	42.686	51.360	51.517
ROCCH-EER – objective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	7.165	46.808	41.564	48.515	44.087	48.402	25.575	25.414	23.037	40.737
	male	1.046	49.713	46.847	49.695	45.377	49.976	17.532	16.910	18.131	43.295
VCTK (common)	female	2.749	47.635	44.095	49.243	45.745	48.025	30.455	29.282	31.130	49.623
	male	0.958	49.955	45.803	49.832	45.516	49.949	23.988	27.559	28.411	46.918
VCTK (different)	female	4.842	47.837	43.160	49.888	48.455	49.398	29.905	29.283	29.246	50.000
	male	1.970	49.998	46.388	49.980	48.005	50.000	27.994	27.192	35.428	48.615
ROCCH-EER – subjective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	14.974	34.434	30.193	30.848	41.195	29.504	23.231	30.052	31.790	38.131
	male	14.077	40.666	40.357	32.857	37.490	38.548	41.242	31.662	39.838	43.201
VCTK (common)	female	14.747	44.673	41.373	41.285	49.303	43.588	40.403	40.795	43.767	49.498
	male	12.305	41.405	37.796	37.961	41.892	41.450	38.739	35.709	44.268	45.608
VCTK (different)	female	15.103	44.011	44.901	46.283	49.934	43.590	42.002	42.035	47.698	50.000
	male	10.922	42.102	40.054	41.433	39.598	43.105	42.831	39.728	47.801	47.880
$C_{lr}^{min}$ – objective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	0.183	0.995	0.969	0.996	0.980	0.996	0.686	0.692	0.617	0.936
	male	0.041	0.999	0.983	0.997	0.985	1.000	0.498	0.491	0.498	0.898
VCTK (common)	female	0.091	0.994	0.976	0.999	0.982	0.991	0.807	0.799	0.770	0.996
	male	0.036	1.000	0.988	0.998	0.987	1.000	0.713	0.720	0.699	0.973
VCTK (different)	female	0.169	0.998	0.981	1.000	0.996	0.999	0.795	0.798	0.743	1.000
	male	0.072	1.000	0.992	1.000	0.996	1.000	0.720	0.729	0.853	0.989
$C_{lr}^{min}$ – subjective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	0.521	0.879	0.814	0.866	0.945	0.823	0.720	0.813	0.840	0.944
	male	0.500	0.904	0.926	0.871	0.926	0.913	0.935	0.831	0.928	0.952
VCTK (common)	female	0.520	0.956	0.933	0.941	0.996	0.950	0.909	0.907	0.955	0.998
	male	0.454	0.944	0.914	0.865	0.948	0.947	0.910	0.872	0.929	0.974
VCTK (different)	female	0.514	0.940	0.975	0.990	0.999	0.957	0.945	0.925	0.967	1.000
	male	0.439	0.927	0.922	0.908	0.909	0.922	0.930	0.921	0.989	0.984
$C_{lr}$ – objective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	26.793	151.822	145.527	156.009	166.758	151.903	115.572	119.482	94.616	155.727
	male	15.303	166.658	174.096	158.899	155.661	168.815	106.444	110.912	88.902	156.919
VCTK (common)	female	0.866	162.531	161.629	176.720	172.027	157.730	93.959	107.851	51.872	170.605
	male	1.041	190.136	184.643	170.676	172.460	186.497	99.336	107.514	68.065	156.197
VCTK (different)	female	1.495	146.929	148.254	156.986	156.706	142.854	93.164	103.681	41.045	171.578
	male	1.817	167.824	162.544	165.986	157.562	164.769	101.697	111.860	79.276	162.578
$C_{lr}$ – subjective											
Data	Gender	Orig	B1	O1	M1	S2	A2	B2	D1	I1	K2
LibriSpeech	female	0.901	0.987	0.970	0.977	1.006	0.970	0.947	0.962	0.966	1.004
	male	0.912	1.008	1.009	0.985	1.006	0.998	1.009	0.975	1.001	1.027
VCTK (common)	female	0.944	1.052	1.033	1.024	1.072	1.041	1.019	1.024	1.039	1.080
	male	0.916	1.033	1.016	1.018	1.033	1.028	1.017	0.999	1.041	1.050
VCTK (different)	female	0.952	1.043	1.049	1.056	1.085	1.049	1.031	1.037	1.066	1.091
	male	0.922	1.026	1.024	1.027	1.024	1.040	1.029	1.018	1.049	1.063

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