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Privacy and utility of x-vector based speaker anonymization

Brij Mohan Lal Srivastava, Mohamed Maouche, Md Sahidullah, Emmanuel Vincent, Aurélien Bellet, Marc Tommasi, Natalia Tomashenko, Xin Wang, and Junichi Yamagishi

Abstract—We study the scenario where individuals (speakers) contribute to the publication of an anonymized speech corpus. Data users leverage this public corpus for downstream tasks, e.g., training an automatic speech recognition (ASR) system, while attackers may attempt to de-anonymize it using auxiliary knowledge. Motivated by this scenario, speaker anonymization aims to conceal speaker identity while preserving the quality and usefulness of speech data. In this article, we study x-vector based speaker anonymization, the leading approach in the VoicePrivacy Challenge, which converts the speaker’s voice into that of a random pseudo-speaker. We show that the strength of anonymization varies significantly depending on how the pseudo-speaker is chosen. We explore four design choices for this step: the distance metric between speakers, the region of speaker space where the pseudo-speaker is picked, its gender, and whether to assign it to one or all utterances of the original speaker. We assess the quality of anonymization from the perspective of the three actors involved in our threat model, namely the speaker, the user and the attacker. To measure privacy and utility, we use respectively the linkability score achieved by the attackers and the decoding word error rate achieved by an ASR model trained on the anonymized data. Experiments on LibriSpeech show that the best combination of design choices yields state-of-the-art performance in terms of both privacy and utility. Experiments on Mozilla Common Voice further show that it guarantees the same anonymization level against re-identification attacks among 50 speakers as original speech among 20,000 speakers.

Index Terms—speaker anonymization, privacy, linkability, voice conversion

I. INTRODUCTION

Speech is a rich source of personal information including sensitive attributes such as identity [1], accent [2], or pathological condition [3]. When the speaker’s goal is not biometric authentication but some other voice-based interaction, for example, exchanging with voice assistants or customer helplines, speaker anonymization is desirable. Indeed, the availability of efficient techniques to infer these attributes from speech as well as recent advances in voice cloning [4] pose severe privacy and security risks [5].

Throughout this article, we consider the following threat model. Given a public dataset of anonymized speech contributed by several speakers, an attacker records/finds a sample of speech of a speaker and attempts to find which utterances in the anonymized dataset are spoken by this speaker, possibly leveraging some knowledge about the anonymization method. A good speaker anonymization method must defeat such link-age attacks by concealing speaker identity, while preserving the utility of speech for data users as measured for instance by the perceived speech naturalness and/or the performance of downstream tasks such as training an automatic speech recognition (ASR) system. Figure 1 shows the three actors involved in this model, namely the speaker, the attacker and the user, along with their actions. The goals of the speaker and the user are intimately linked, while the attacker operates independently.

Speaker anonymization methods have been studied for just over a decade. They include noise addition [7], speech transformation [8], voice conversion [9]–[11], speech synthesis [12], [13], or adversarial learning [14]. In this study, we focus on x-vector based anonymization [13], [15], which converts the original speaker’s voice into that of a target (pseudo-)speaker, due to the naturalness of its output and its promising results so far. In order to implement and assess such an anonymization method, the following questions arise from the speaker’s and user’s perspectives: Q1: How to optimally choose and assign the target pseudo-speaker? Q2: How well is utility preserved? Q3: How much residual speaker information remains? Furthermore, the attacker must address the following questions: Q4: Can privacy protection be defeated using some knowledge of the anonymization method? Q5: How does the number of possible speakers affect the re-identification performance?

In this article, we extend the two target pseudo-speaker generation strategies in [13] (fully random, or at a fixed distance from the original as measured by cosine distance between x-vectors) into a whole family of strategies based on four design choices: the distance metric between x-vectors, the region of x-vector space where the pseudo-speaker is picked, its gender, and whether to assign it to one or all utterances of the original speaker. Our experiments suggest an optimal combination of design choices to balance privacy and utility (answering Q1). We train and/or evaluate ASR models on anonymized speech to assess utility (answering Q2). We show that some speaker information remains in the pitch sequence and apply two different pitch transformation techniques to remove it (answering Q3). We conduct these experiments for three types of attackers [16], where stronger attackers

1Legally speaking, the term “anonymization” refers to a method that fully achieves this goal. Following [6], we use it in a broader sense to refer to a method that aims to achieve this goal, even when it has failed to do so.
have more knowledge about the anonymization method (answering Q4). Finally, we conduct additional experiments with more than 20,000 possible speakers (answering Q5). These contributions significantly extend our preliminary study [17], which provided less detail, did not include utterance- vs. speaker-level target assignment and pitch transformation, did not evaluate privacy against the strongest (Semi-Informed) attacker or with a large number of possible speakers, and did not evaluate utility for ASR training.

The structure of the article is as follows. In Section II, we introduce x-vector based anonymization and position it among other related anonymization methods. Section III presents the four considered design choices. Sections IV and V describe the main experimental setup and the corresponding results. Experiments with more speakers are conducted in Section VI. We conclude in Section VII.

II. X-VECTOR BASED ANONYMIZATION

Speaker anonymization aims to conceal the speaker’s identity from a speech signal such that it cannot be used to clone the speaker’s voice or to re-identify the speaker through automatic speaker verification (ASV) or automatic speaker identification (ASI). Early methods based on voice conversion required both the original and the target speaker to be part of the training set for the voice conversion system. Jin et al. [9] convert all speakers into a single target. Bahmaninezhad et al. [11] convert a given speaker into the average of all speakers of the same gender. Pobar and Ipišć [10] pre-train a set of speaker transformations and identify the speaker at test time to select one of the corresponding transformations. These methods are hardly applicable in practice since, in the context of anonymization, the amount of speech from the original speaker is often limited to one utterance. To relax this constraint, Magaríños et al. [18] find the closest source speaker in the training set and apply one of the corresponding transformations, while Justin et al. [12] transcribe speech into a diphone sequence and re-synthesize it using a single target. Although they do not require the original speaker to belong to the training set anymore, these two methods suffer from three limitations. First, they still result in a limited set of target speakers or speaker transformations, which prevents the original speaker from choosing an arbitrary unseen speaker as the target. Second, using a real speaker’s voice as the target raises ethical concerns. Third, the phonetic transcription step in [12] is error-prone. This motivates the objective of converting the original speaker’s voice into an arbitrary, imaginary pseudo-speaker’s voice without relying on a transcription step. Speaker embeddings such as x-vectors [19] (a low-dimensional representation extracted from an intermediate layer of an ASI model) provide the continuous representation needed to define and generate such pseudo-speakers.

Fang et al. [13] address this objective using a speaker-independent speech synthesis system. They select x-vectors within an external pool of speakers and average them to obtain a target pseudo-speaker x-vector. This x-vector, along with a representation of the original linguistic and intonation contents, is provided as input to a neural source-filter (NSF) based speech synthesizer [20] to produce anonymized speech.

In the following, we use the anonymization system shown in Fig. 2, that is a variant of the one in [13]. This system represents speaker identity, linguistic content and intonation using x-vectors, bottleneck (BN) features B [21] (a low-dimensional representation extracted from an intermediate layer of an ASR model) and pitch sequences p, respectively. It comprises four steps: Step 1 (Feature extraction) extracts pitch and BN features and the x-vector from the input signal. Step 2 (X-vector anonymization) generates a target x-vector \( \mathbf{v}^* \) by averaging \( N^* \) candidate x-vectors from an external pool.

\[ \mathbf{v}^* \]

Following [13], we use raw x-vectors to represent speaker identity instead of x-vectors compressed and rotated by linear discriminant analysis (LDA), as classically done in the context of ASV. Unless the projected dimension is carefully chosen after several experiments, the impact of the LDA transformation on speaker-specific information cannot be ascertained. Hence we defer experiments with LDA-transformed x-vectors to a future study.

Fig. 1. Considered threat model. Speakers anonymize speech to conceal their identity before publication; attackers use biometric technology and knowledge of the anonymization method to re-identify it; users (e.g., speech technology companies) use the published data for downstream tasks such as ASR training.

Fig. 2. General architecture of the anonymization system.
of speakers.³ Step ³ (Pitch conversion) is an optional step which receives the target pitch statistics from the anonymization module and transforms the original pitch sequence into \( p^* \). Step ⁴ (Speech synthesis) synthesizes a speech waveform from the anonymized x-vector \( v^* \) and the original B and p (or optionally \( p^* \)) features using an acoustic model (AM) and the NSF model. With the exception of Step ³ which is new (see Section V-D), this system is identical to the first anonymization baseline for the VoicePrivacy Challenge [6]. We refer to [22] for details on the feature dimensions and the architectures of the models in Steps ¹ and ⁴.

We note that there have been other interesting attempts to generate a target pseudo-speaker x-vector for speaker anonymization in the systems submitted to the first VoicePrivacy Challenge. Mawalim et al. [23] modified the significant elements of the source speaker x-vector that were determined using singular value decomposition and variant analysis to anonymize the identity. Perero-Codosero et al. [24] transformed the original x-vector using an autoencoder with adversarial training to suppress speaker, gender and accent information. Turner et al. [25] fitted a Gaussian mixture model based generative model over the external pool of speakers, and then proposed to sample target x-vectors from this model to preserve the distributional properties of x-vectors. Readers are referred to Tomashenko et al. [26] for an in-depth analysis of the objective and subjective evaluation results achieved by the two challenge baselines and the 16 submissions.

### III. ANONYMIZATION DESIGN CHOICES

Now given the ability to generate arbitrary external targets in Step ² (yellow box in Fig. 2), the question arises of which strategy the speaker shall employ to select the candidate x-vectors and achieve a suitable privacy-utility tradeoff. Fang et al. [13] select candidate x-vectors at random within the whole pool or within a fixed interval of distances from the original x-vector. Han et al. [15] select a single target x-vector at random within a maximum distance from the original x-vector. In the following, we expand these initial strategies into a broader range of strategies governed by the choice of the distance metric between x-vectors, the region of x-vector space where the candidates are selected, their gender, and the assignment of the resulting target x-vector to one or all utterances of the original speaker. These four design choices, which are illustrated in Fig. 3, are detailed below. For the sake of focus, we do not explore other design choices such as the size or the diversity of the anonymization pool.

#### A. Distance metric: cosine vs. PLDA

To design advanced candidate selection strategies, the speaker must first choose a distance metric which dictates the properties of the x-vector space. We compare two such metrics.

The first one is the cosine distance, which was used by [13]. For a pair of x-vectors \( \omega_i \) and \( \omega_j \), it is defined as

\[
d_{\text{cos}}(\omega_i, \omega_j) = 1 - \frac{\omega_i \cdot \omega_j}{||\omega_i||_2 ||\omega_j||_2},
\]

³There is no guarantee that averaging produces a valid x-vector, but all our experiments show that the synthesized anonymized speech is of good quality.

![Diagram](image)

Fig. 3. Zoomed-in view of the x-vector anonymization step in Fig. 2 showing the design choices for the generation of the target x-vector.

The second metric is based on probabilistic linear discriminant analysis (PLDA) [27], that is the log-likelihood ratio of the hypotheses that \( \omega_i \) and \( \omega_j \) belong to the same speaker (\( H_s \)) vs. different speakers (\( H_d \)). Previous studies [28] have shown that PLDA yields state-of-the-art performance as the x-vector similarity metric in the context of ASV. This is attributed to its formulation which estimates the factorized within-speaker and between-speaker variability in speaker space, making it a superior metric even for short utterances [29]. More specifically, PLDA models x-vectors \( \omega \) as \( \omega = m + Vy + Dz \), where \( m \) is the center of the x-vector space, the columns of \( V \) capture speaker variability (eigenvoices) with \( y \) depending only on the speaker, and the columns of \( D \) encode channel variability (eigenchannels) with \( z \) varying from one recording to another. The parameters \( m, V \) and \( D \) are trained on x-vectors extracted using the x-vector extractor in Step ¹ from the dataset used to train that extractor itself (see [22] for details on this dataset). The log-likelihood ratio score

\[
d_{\text{PLDA}}(\omega_i, \omega_j) = \log \frac{p(\omega_i, \omega_j | H_s)}{p(\omega_i, \omega_j | H_d)}
\]

(2)

can be computed in closed form [30]. We propose to use \( -d_{\text{PLDA}} \) as the “distance” between a pair of x-vectors.

#### B. Proximity: random, far, near, dense, or sparse

We propose three alternative criteria resulting in five different “proximity” choices to restrict the region of x-vector space from which candidate x-vectors are selected.

1) Random: The simplest candidate x-vector selection strategy is to select \( N^* \) x-vectors with a given gender uniformly at random from the pool. Note that this strategy does not allow us to choose particular regions of interest in the x-vector space.

2) Far/near: Alternatively, the chosen distance metric can be used to find candidate x-vectors which resemble most (near) or least (far) the original speaker \( v \). In essence, we rank all the x-vectors in the pool in increasing order of their distance from \( v \) and select either the top \( N \) (near) or the bottom \( N \) (far). To introduce some randomness, \( N^* < N \) x-vectors are selected out of these \( N \) uniformly at random.

3) Dense/sparse: Another alternative is to identify clusters of x-vectors in the pool and rank them based on their cardinality. We construct these clusters using the Affinity Propagation [31] algorithm (see detailed procedure in Section IV-B). We filter out the cluster which is closest to the original speaker, then randomly select one cluster among those with most
(dense) or least (sparse) members.\(^4\) We then randomly select half of the members of that cluster.

In all five cases, the selected candidate x-vectors are averaged to obtain the target (pseudo-speaker) x-vector \(v^\ast\).

C. Gender selection: same, opposite, or random

In practice, instead of applying one of these five proximity choices to the entire speaker pool, we apply it to a gender-dependent pool which consists of either all males or all females of the original pool. We propose three possible gender selection choices: same where all speakers in the pool have the same gender as the original speaker; opposite where they all have the opposite gender; and random where either of the two gender-dependent pools is selected at random. This allows us to avoid averaging candidate x-vectors from both genders with each other, and to assess the impact of gender selection on privacy and utility.

D. Assignment: speaker- or utterance-level

The generation of the anonymized waveform is conditioned upon the x-vector sequence, whose length is equal to the number of frames in the original utterance. All the x-vectors in this sequence are identical to each other to indicate a single pseudo-speaker throughout the utterance. In theory, these x-vectors should also be identical across all utterances spoken by this pseudo-speaker but, according to [32], x-vectors also contain channel, duration, and phonetic information, in addition to speaker and gender. Hence, the x-vectors computed for different utterances may exhibit some variations due to utterance-specific properties. To assess the effect of these variations on privacy and utility, we propose two assignment strategies for the target x-vector: speaker-level (perm) or utterance-level (rand). In the former case, we average the utterance-level x-vectors of all utterances of the original speaker into a single speaker-level x-vector \(v^s\), we generate a corresponding target x-vector \(v^\ast_s\), and we use it to anonymize all utterances of that speaker. In the latter case, we consider the utterance-level x-vector \(v^u_u\) for each utterance \(u\) of the original speaker, we generate a corresponding target x-vector \(v^\ast_u\) (using the same distance metric, proximity, and gender across all utterances), and we use it to anonymize that utterance only.

IV. Experimental setup

The VoicePrivacy Challenge [6] assumed that the attacker does not have access to the anonymization system and that the user is unaware that speech has been anonymized. Privacy and utility were consequently assessed using an ASV system and an ASR system trained on original (non-anonymized) speech. This resulted in overestimated privacy and underestimated utility with respect to an attacker or a user who have access to the anonymization scheme [16]. Also, the utility for ASR training was not evaluated. Following [16], we advocate for a complete study of the utility/privacy trade-off, which is key to the success of downstream tasks.

Table I

<table>
<thead>
<tr>
<th>Common Voice-enroll</th>
<th>Number of speakers</th>
<th>24,610</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of utterances</td>
<td>320,085</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Common Voice-trial</th>
<th>Number of speakers</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of utterances</td>
<td>4,696</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of trials</th>
<th>Same-speaker trials</th>
<th>4,696</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Different-speaker trials</td>
<td>115,563,864</td>
</tr>
</tbody>
</table>

B. Algorithm settings

The dense and sparse anonymization choices are implemented as follows. We use Affinity Propagation [31] to cluster the speakers in the external pool. This non-parametric clustering method determines the number of clusters automatically via a message passing algorithm. Two parameters govern the number of clusters: the preference parameter assigns a higher weight to samples which are likely candidates for centroids, and the damping factor weights the so-called responsibility and availability messages. In our experiments, equal preference is assigned to all samples and the damping factor is set to

\(^4\)Note that the terms sparse and dense do not directly reflect the density of x-vectors, since they do not take the diameter of the clusters into account. However, we find that this relation holds in practice.

\(^5\)The VoicePrivacy Challenge involves development and evaluation sets built from LibriSpeech and VCTK. Due to space limitations, we focus on LibriSpeech.

\(^6\)The SNR was computed using the WADA-SNR [39] algorithm available at https://gist.github.com/johnmeade/d8d2c67b87da95cd2535e5c21387e75.
Out of 1,160 speakers in the pool, 80 clusters are found, including 46 male and 34 female. The number of speakers per cluster ranges from 6 to 36. Candidate x-vector selection is achieved by picking either the 10 clusters with least members (sparse) or the 10 clusters with most members (dense). The remaining clusters are ignored. During anonymization, one of the 10 clusters is selected at random and 50% of its members are averaged to produce the target x-vector.

C. Privacy evaluation

As explained in Section I, privacy protection can be seen as a contest between two entities: a speaker who publishes anonymized utterances, and an attacker who attempts to uncover the speaker's identity by comparing these utterances with utterances whose speaker is known. Following the classical ASV terminology adopted in the VoicePrivacy Challenge, these are called trial and enrollment utterances, respectively, and each such comparison is called a trial. The attacker has full control over the enrollment set and the speaker identities within it. Hence he/she may use some knowledge about the anonymization scheme to transform the enrollment data and reduce the mismatch with the trial data. To assess the strength of anonymization against attackers with increasing knowledge, we perform the evaluation in four scenarios:

- **Baseline:** The speaker does not perform any anonymization. The attacker uses original speech for enrollment and an ASV system trained on original speech. This offers the lowest possible privacy protection.
- **Ignorant:** The speaker anonymizes his/her speech, unknown to the attacker who still uses original speech for enrollment and an ASV system trained on original speech.
- **Lazy-Informed:** The speaker anonymizes his/her speech. The attacker anonymizes the enrollment data using the same anonymization system and the same design choices. However, he/she is not aware of the random numbers drawn by the speaker to obtain the random target gender (Section III-C) or the candidate x-vectors (Section III-B). Hence, different pseudo-speakers are assigned to the trial and enrollment utterances of a given speaker.
- **Semi-Informed:** The speaker anonymizes his/her speech. The attacker anonymizes the enrollment data using the same system and design choices. In addition, he/she anonymizes the training dataset for the ASV system and re-trains it. This scenario is the one in which the speaker is most “vulnerable” despite anonymization, hence we consider it as the most trustworthy assessment of privacy.

In Section V, privacy is assessed in terms of the linkability [40], [41], denoted as \( D_{\theta} \), achieved by an x-vector-PLDA system trained on the train-clean-360 subset of LibriSpeech (anonymized in the Semi-Informed scenario, original otherwise). This metric computes the overlap between the distributions of PLDA scores of same-speaker and different-speaker trials. It behaves similarly to the equal error rate (EER) and log-likelihood ratio cost function [42] used in the VoicePrivacy Challenge, but it does not rely on any restrictive assumption (e.g., threshold-based decision) which makes it a more trustworthy metric [41]. For the sake of reproducibility, we use the same set of trials as in [6].

Formally, the local linkability metric \( D_{\theta} \) for two random utterances \( i \) and \( j \) with a score \( \theta = d_{\text{cos}}(\omega_i, \omega_j) \) or \( \theta = -d_{\text{PLDA}}(\omega_i, \omega_j) \) is defined as \( p(H_s | \theta) - p(H_d | \theta) \). When the local metric is negative, an attacker can deduce with some confidence that the two utterances are from different speakers. The authors in [40] argued that the local metric should estimate the strength of the link described by a score rather than measure how much a score describes different-speaker relationships. Therefore they proposed a clipped version of the difference:

\[
D_{\theta} = \max(0, p(H_s | \theta) - p(H_d | \theta)).
\]  (3)

The global linkability metric \( D_{\psi} \) is then defined as the mean value of \( D_{\theta} \) over all same-speaker scores:

\[
D_{\psi} = \int p(\theta | H_s) \cdot D_{\theta}(\theta) \, d\theta.
\]

In practice, \( D_{\theta} \) is rewritten as \((2 \cdot \alpha \cdot \text{ln}(\theta))/\left(1 + \alpha \cdot \text{ln}(\theta)\right) - 1\) where the likelihood ratio \( \text{ln}(\theta) = p(\theta | H_s)/p(\theta | H_d) \) and the prior probability ratio \( \alpha = p(H_s)/p(H_d) \) and \( p(\theta | H_s) \) and \( p(\theta | H_d) \) are computed via one-dimensional histograms.

In Section VI, we also evaluate the average rank of the true speaker and the top-k precision achieved for closed-set ASI. Instead of training speaker classification systems on subsets of Common Voice, which would overfit the speakers therein, we compute the PLDA scores between each trial utterance and all enrollment utterances (one per speaker, including the true speaker) using the same x-vector and PLDA models as in Section V and sort them in decreasing order. The higher the rank and the lower the top-k precision, the higher the privacy.

D. Utility evaluation

In Section V-A, we evaluate the utility for ASR decoding in terms of the word error rate (WER) achieved by an ASR system trained on the train-clean-360 subset of LibriSpeech and compared to the anonymized utterances. In Sections V-B and V-C, we evaluate the utility both for ASR decoding and training in terms of the WER achieved by an ASR system trained either on the original or the anonymized train-clean-360 dataset and used to decode either original or anonymized speech. For more details on the ASR system architecture, see [6]. A lower WER indicates higher utility. The 95% confidence
interval on the WER varies from $\pm 0.2\%$ for the lowest WER values to $\pm 0.4\%$ for the highest ones.

V. RESULTS AND DISCUSSION

The design choices introduced in Section III result in 54 possible combinations, among which 48 combinations correspond to 2 distances $\times$ 4 non-random proximities $\times$ 3 gender selections $\times$ 2 assignments, and 6 combinations correspond to random proximity with 3 gender selections $\times$ 2 assignments. To assess the impact of these choices, our experiments are organized according to the three actors in our threat model. First, the speaker finds the two most promising combinations of design choices on the development set in terms of privacy in the Ignorant and Lazy-Informed scenarios and utility for ASR decoding. This is motivated by the high computational cost of anonymizing the train-clean-360 subset of LibriSpeech and retraining ASV and ASR systems on it, which prevents the evaluation of privacy in the Semi-Informed scenario and utility for ASR training for all 54 combinations. Second, the user assesses the utility of these two combinations for both ASR training and decoding. Third, the attacker quantifies the resulting privacy in the Semi-Informed scenario, which leads us to identify the best combination among these two. Finally, we show how the proposed pitch transformation further improves privacy.

A. Speaker’s perspective

We first evaluate the design choices from the speaker’s perspective in terms of privacy in the Ignorant and Lazy-Informed scenarios and utility for ASR decoding on the development set. The results are displayed in the form of swarm plots, i.e., scatter plots where each dot represents the privacy or utility value associated with one combination of design choices. In order to avoid overlapping dots with similar values, the dots are spread horizontally.

1) Distance: Figure 4 evaluates the effect of the chosen distance metric on privacy. We observe that both cosine distance and PLDA result in similarly low linkability in the Ignorant case but PLDA marginally outperforms cosine distance (i.e., it results in a lower linkability) in the Lazy-Informed case. Since both distance measures perform similarly in terms of utility (see Fig. 9(a)), PLDA has an advantage. Therefore we consider only PLDA as the distance metric in the following experiments.

2) Proximity: Next, we assess the five choices of target proximity described in Section III-B, namely random, near, far, sparse and dense. The distance metric is fixed to PLDA and the values of $N$ and $N^*$ are fixed to 200 and 100, respectively.\(^{10}\)

We observe in Fig. 5 that, although selecting candidate x-vectors far from the original speaker achieves the lowest linkability in the Ignorant case together with the random strategy, it is largely outperformed in the Lazy-Informed case by selection from sparse or dense clusters and by the random strategy. This shows that clustering based pseudo-speaker mapping results in more robust anonymization as compared to simple distance-based mapping.

Compared to the sparse selection strategy, the dense strategy provides comparable privacy protection in the Lazy-Informed case, but much higher utility (see Fig. 9(b)). This can be attributed to the fact that speakers in sparse clusters stand out more from the crowd than those in dense clusters, therefore they are more likely to suffer from poor ASR performance.

Finally, random target selection yields similar privacy protection in the Lazy-Informed case and slightly better utility as compared to dense. Hence we consider the random and dense strategies to be the best choices for proximity.

3) Gender selection: We now investigate the gender selection strategy described in Section III-C. The distance is fixed to PLDA and proximity to dense or random. As per the results shown in Fig. 6 it is hard to find the best choice for gender selection in terms of privacy since the linkability is not consistently lower for any specific choice.

In order to make a suitable choice, we introduce the additional requirement that the chosen anonymization scheme obfuscates the original speaker’s gender. The different anonymization schemes can be visually compared in Fig. 7. Same gender selection (Fig. 7 (b)) causes male and female clusters to move apart. A similar result is observed with opposite gender selection (not shown in the figure). On the

\(^{10}\)We noticed a sharp decline in utility for smaller values of $N^*$. 
contrary, random gender-selection (Fig. 7(c) and 7(d)) results in a non-separable boundary between genders.

Furthermore, we conduct gender identification experiments over the original and anonymized x-vectors shown in Fig. 7 to measure the degree of gender obfuscation caused by same vs. random gender selection. We employ the k-nearest neighbour algorithm with 5-fold cross-validation to predict the gender of speakers in the LibriSpeech train-clean-360 dataset which contains 921 speakers. The mean cross-validation accuracy for each dataset reported in Table II corroborates the visual observations in Fig. 7.

4) Assignment: Finally the choice of pseudo-speaker assignment is examined from the speaker’s perspective as described in Section III-D. The distance is fixed to PLDA, proximity to dense and gender selection to random. The results reported in Fig. 8 show that utterance-level assignment results in lower linkability than speaker-level assignment. However, the WER resulting from utterance-level assignment is higher than from speaker-level assignment (see Fig. 9(d)).

In the following, in order to conform with the requirements of the VoicePrivacy Challenge [22, Section 3.2], we choose speaker-level assignment. This ensures that “all trial utterances from a given speaker appear to be uttered by the same pseudo-speaker”.

Based on these indications, the speaker may choose specific parameters according to their application needs. For the sake of further experimentation, we choose distance as PLDA, proximity as random or dense, gender selection as random and assignment as speaker-level to be the two best combinations of design choices based on our observations.

B. User’s perspective

We now present complementary results from the user’s perspective. Recall that in our threat model the user exploits the anonymized speech data for some downstream task. His/her primary concern is hence the utility of the data for that task. So far, we have only evaluated the utility for ASR decoding using an ASR system trained on the original train-clean-360 dataset (see Fig. 9). We now evaluate the utility for ASR decoding using an ASR system trained on anonymized data, as well as the utility for ASR training. To do so, we anonymize the train-clean-360 dataset using either of the two best combinations of design choices, and we retrain the ASR system on it.

Figure 10 shows the resulting utility values. The four bars in each plot represent the four decoding scenarios: OO indicates original (non-anonymized) speech decoded by the ASR model trained on original speech, AO indicates anonymized speech decoded by the ASR model trained on anonymized speech.
decoding by the ASR model trained on original speech. OA indicates original speech decoded by the ASR model retrained on anonymized speech, and AA indicates anonymized speech decoded by the ASR model retrained on anonymized speech.

We observe a WER degradation in the AO and OA scenarios, which indicates a mismatch between training and test data. The degradation is higher when original speech is decoded using the retrained model (OA) than when anonymized speech is decoded using the original model (AO). This asymmetry suggests a “loss of generalization” of the ASR model trained on anonymized speech, due to the unintentional exclusion of certain factors of variability of original speech.

Fortunately, the WERs on the test set in the AA scenario are almost as low as those in the OO scenario. This indicates that anonymization yields viable speech data for ASR training and ASR decoding with a WER similar to original speech, provided that training and decoding are both conducted on anonymized speech. No significant difference is observed depending on the proximity choice made by the speaker.


c. Attacker’s perspective

Finally, we present complementary results from the attacker’s perspective. The primary objective of the attacker is to find the original speaker’s identity of anonymized speech utterances, i.e., to achieve high linkability. So far, we have only reported the linkability achieved by Ignorant and Lazy-Informed attackers on the development set. We now present the results achieved by these attackers and by a Semi-Informed attacker on both the development and test sets.

The results for the two best combinations of design choices are shown in Fig. 11. We observe that the linkability increases as the strength of the attacker increases. It goes up to 0.44 with random proximity, but stays below 0.22 with dense proximity, even for the strongest (Semi-Informed) attacker. This indicates the robustness of dense over random proximity. Therefore, we ultimately recommend the following combination of choices to the speaker: **PLDA** distance, **dense** proximity, **random** gender selection, and **speaker-level** assignment. We recall that the latter choice is a requirement set by the VoicePrivacy challenge. Whenever **speaker-level** assignment is not required, we recommend **utterance-level** assignment for higher privacy.


d. Pitch conversion

Sticking with the best combination of design choices, we bring one last improvement: we explore three pitch conversion methods to further enhance privacy and increase the naturalness of anonymized speech. Indeed, the pitch sequence $p$ might reveal some information about the speaker [44] which is carried over to the synthesized speech. Also, keeping the pitch
sequence $p$ unchanged while possibly changing the gender of the x-vector results in inconsistent features which affect the naturalness of the synthesized speech.

The three conversion methods operate on nonzero pitch values only. Indeed, zero pitch values correspond to unvoiced or silent frames, and must remain equal to zero to preserve the phonetic content of the utterance. Conversely, nonzero pitch values must remain nonzero. In the rest of this section, the term “pitch sequence” and the notation $p$ refer to a sequence stripped off its zero values.

The first method called logarithm Gaussian pitch conversion [45] was recently employed in [46] for voice anonymization. The target pitch sequence $p^{*}$ is obtained by linearly scaling the original pitch sequence $p$ in the logarithmic domain as

$$
\log(p^{*}) = \log(p) - \frac{\mu_{src}}{\sigma_{src}} \sigma_{tgt} + \mu_{tgt},
$$

where $\mu_{src}$, $\sigma_{src}$ are the mean and standard deviation of $p$, and $\mu_{tgt}$, $\sigma_{tgt}$ are the mean and standard deviation of the target pseudo-speaker’s pitch “sequence” $p_{ps}$. The latter is obtained by concatenating the pitch sequences of all utterances of the $N^{c}$ candidate speakers composing the pseudo-speaker; it is stored by the x-vector anonymization module (Step 2 in Fig. 2) and passed to the pitch conversion module (Step 3).

In addition, we propose two other methods, which we call percentile and minmax based pitch conversion. Percentile based pitch conversion maps each percentile of the original pitch distribution to the corresponding percentile of the target pitch distribution. To do so, the sequences $p$ and $p_{ps}$ are sorted in ascending order, yielding $p_{sorted}$ and $p_{ps_{sorted}}$. Each value $p[i]$ in the original sequence is converted into a percentile $\varrho[i]$:

$$
\varrho[i] = \frac{\text{rank of } p[i] \text{ in } p_{sorted}}{\text{length}(p_{sorted})} \times 100.
$$

Then, the converted pitch value $p^{*}[i]$ corresponding to $\varrho[i]$ is picked in $p_{ps_{sorted}}$ as

$$
\left\lfloor \frac{\text{length}(p_{ps_{sorted}}) \times \varrho[i]}{100} \right\rfloor
$$

where $\lfloor \cdot \rfloor$ denotes rounding down to the nearest integer. This mapping is an instance of one-dimensional optimal transport between the two distributions [47]. To the best of our knowledge, this pitch conversion method is new.

Minmax based pitch conversion linearly scales the range of pitch values, such that the minimum and maximum values in the original sequences are mapped to the minimum and maximum values of the target pseudo-speaker:

$$
\left\lfloor \frac{(p[i] - \min(p)) \times \max(p_{ps}) - \min(p_{ps})}{\max(p) - \min(p)} + \min(p_{ps}) \right\rfloor.
$$

One benefit of percentile or minmax based conversion is that the converted pitch values belong to the range of pitch values for the $N^{c}$ candidate speakers composing the pseudo-speaker, while in case of Gaussian normalization some converted pitch values may be beyond that range or even beyond the range of valid pitch values for male or female speakers.

It is observed in Fig. 12(a) that logarithm Gaussian pitch conversion and to a lesser extent minmax based conversion significantly increase the WER, while percentile based conversion maintains a WER close to the original. Figure 12(b) shows that percentile and minmax based conversion substantially improve privacy, especially against the Semi-Informed attacker, while logarithm Gaussian conversion results in a more modest improvement or no improvement. We conclude that percentile based conversion is a suitable pitch conversion method which increases privacy with no significant loss of utility. According to informal listening results (not show in the figure), it also improves the naturalness of cross-gender voice conversion.

Overall, the experiments in Section V exhibited the benefits of the proposed improvements to x-vector based voice conversion in terms of privacy against the strongest (Semi-Informed) attacker. Specifically, x-vector based voice conversion with the best combination of design choices and with percentile based pitch conversion reduces the attacker’s linkability by one order of magnitude with respect to original speech. This is to be contrasted with signal processing based methods such as [48] which offer almost no protection against such a strong attacker.
VI. LARGE-SCALE SPEAKER STUDY

Similarly to other studies following the VoicePrivacy Challenge setup, all experiments above have relied on a small set of 29 enrolled speakers. In this section we analyze the attacker’s performance against a larger number of enrolled speakers. This number reflects the attacker’s knowledge: a smaller number means that the attacker was able to narrow down the list of speakers who may have uttered the trial utterances using contextual information.\(^\text{11}\) Our goal is to study whether the speaker’s identity gets hidden in the crowd or is still revealed to some extent within a large set of enrolled speakers.

Previous research has studied the impact of the number of speakers from a voice spoofing perspective where an attacker aims to be accepted through an ASV authentication system by finding the closest (trial) impostor to a given (enrolled) target speaker [49], [50]. The attacker has access to a speech sample of the target speaker and to the ASV scoring mechanism. The authors showed that the chances of acceptance reach up to 50\% as the number of impostors approaches \(10^5\). A similar problem was posed by the Multi-Target Speaker Detection Challenge [51] which aims to identify and assess the membership of a speaker to a set of blacklisted speakers. The authors showed that the performance for both tasks degrades as the number of speakers in the blacklist increases. In the following, we do not assess the worst-case performance like [50]. Instead, we measure the overall speaker recognition performance as the number of different-speaker trials increases manifold.

A. Experimental setup

We use the Mozilla Common Voice English corpus because of its large number of speakers. To the best of our knowledge this is the first time this corpus is used for ASV and privacy related experiments.

As mentioned in Section IV-A, we consider a total population of 24,610 male speakers. Out of these, utterances from 20 speakers are selected as the public trial data subjected to re-identification attack. After computing PLDA scores between the trial and enrollment utterances, we get 4,696 same-speaker scores and 115,563,864 different-speaker scores (see Table I).

We measure the attacker’s performance against an increasing number of enrolled speakers. In the first step, we select for enrollement the same 20 speakers as for trial, and we use the corresponding same- and different-speaker scores. In the second step, we add 20 other speakers for enrollement and we include the corresponding different-speaker scores. In the following steps, we double the number of other speakers at each step, i.e., the total number of enrolled speakers increases from 20 to 20,500. The added speakers are randomly sampled 5 times from the entire speaker population to avoid any bias.

B. Open-set results

Figure 13 reports the performance of different attackers in terms of linkability. The linkability of original speech is equal to 0.80 with 20 speakers and decreases to 0.70 with more than a few hundred speakers. The linkability of anonymized speech is much lower. For Ignorant and Lazy-Informed attackers, it starts from 0.18 and decreases to 0.06. The linkability curve for the Semi-Informed attacker is surprisingly below those of the two other attackers, but it also follows a decreasing trend.

\[\text{Linkability } D_{\text{sys}}(k) = \frac{1}{k} \sum_{i=1}^{k} \text{Linkability } D_{\text{sys}}(i)\]

\[\text{Baseline} \quad \text{Ignorant} \quad \text{Lazy-Informed} \quad \text{Semi-Informed}\]

\[\begin{array}{cccc}
\text{Number of enrollment speakers} & 10^2 & 10^3 & 10^4 \\
\text{Linkability } D_{\text{sys}} & 0.80 & 0.70 & 0.50 \\
\end{array}\]

\[\text{Fig. 13. Open-set ASV performance of Ignorant, Lazy-Informed and Semi-Informed attackers as a function of the number of enrolled speakers, compared to original speech (Baseline).}\]

C. Closed-set results

The above evaluation in terms of linkability, which assumes that the attackers rely on open-set ASV, hides the fact that the chance of finding the true speaker of a trial utterance decreases very quickly as the number of enrolled speakers increases. To highlight it, we perform closed-set ASI as explained in Section IV-C and report the rank of the true speaker. The higher the rank, the lower the ASI performance. Since increasing the number of speakers is expected to increase the rank, we also report the normalized rank, that is the rank divided by the number of speakers, and the chance-level rank, that is the expected rank when the attacker selects the true speaker at random (see Appendix A).

Figure 14(a) shows that the rank of the true speaker increases almost linearly as a function of the number of speakers. On original speech, it remains much lower than chance-level even with thousands of speakers, which can be attributed to the distinct characteristics of speakers in the population. On anonymized speech, it converges close to the chance-level rank for all attackers. The normalized rank plot in Fig. 14(b) shows that, beyond a few hundred speakers, the Ignorant and Lazy-Informed attackers perform more poorly than chance-level, while the Semi-Informed attacker maintains a consistent performance that is slightly better than chance-level.

In addition, we study the top-\(k\) precision obtained by the attackers compared to the baseline performance for \(k \in \{1, 20\}\). We observe in Fig. 15 that the precision drops much faster on anonymized data than original data, i.e., finding the true speaker of an anonymized utterance among a set of \(S\) speakers is equivalent to finding the true speaker of an original utterance among \(S'\) speakers, where \(S'\) increases at a much faster rate than \(S\). The plot for \(k = 1\) shows that without anonymization the true speaker can be uniquely identified with 40\% accuracy among 20,500 speakers, while after anonymization the risk

\[11\text{The attacker may obtain this contextual information by inspecting the metadata and/or the statistics of the public, anonymized dataset, or by simply listening to individual utterances.}\]
of being uniquely identified becomes negligible beyond a few dozen speakers. For \( k = 20 \), our anonymization scheme provides the same level of protection against a Semi-Informed attacker among 52 speakers than raw speech among 20,500 speakers. Additional results for \( k \in \{10, 50\} \) (not shown here) follow a similar trend.

**VII. CONCLUSION**

Our work aimed to answer three questions from the speaker’s and user’s perspectives, and two questions from the attacker’s perspective to realistically assess the privacy and utility of x-vector based speaker anonymization (see Section I). To answer Q1, we introduced four design choices and studied their effect on the privacy of anonymized speech and its utility for ASR training and decoding. Based on our findings, we recommended the following optimal combination of choices: PLDA distance, dense proximity, random gender selection, and utterance-level assignment (unless otherwise required). To answer Q3, we then investigated three pitch conversion methods for removing the residual speaker information carried by the pitch sequence and to enhance the naturalness of the synthesized speech. While classical logarithm Gaussian conversion resulted in little or no improvement of privacy, the proposed percentile based conversion method significantly improved privacy with little loss of utility. Overall, x-vector based voice conversion with the best combination of design choices and with percentile based pitch conversion reduced the linkability against the strongest (Semi-Informed) attacker by one order of magnitude with respect to original speech (answering Q4), and it increased the WER on LibriSpeech test-clean from 4.1% to 4.8% only in the situation when ASR training and decoding are both conducted on anonymized speech (answering Q2).

To answer Q5, we further evaluated the proposed anonymization scheme as a function of the number of enrolled speakers, which reflects the attacker’s ability to narrow down the list of speakers who may have uttered the trial utterances using contextual information. We conducted closed-set ASI by incrementally adding thousands of speakers in the population and observed that the rank of the true speaker quickly increases and converges close to chance-level after anonymization. Another interesting observation can be made by looking at top-\( k \) precision curves: the loss of precision before anonymization that is seen after adding thousands of speakers in the enrollment set is equivalent to adding only a couple of speakers after anonymization. Specifically, the best combination of design choices offers the same level of protection against re-identification attacks among 52 speakers as original speech among 20,500 speakers.

In the future, we plan to study the worst-case performance of the proposed speaker anonymization scheme and characterize which speakers are easier to re-identify. We also plan to provide analytical lower bounds on privacy by using techniques...
inspired from differential privacy [52].

**APPENDIX A**

**DERIVATION OF THE CHANCE-LEVEL RANK**

Let \( R \in \{1, \ldots, N_{\text{spk}}\} \) be the set of all possible ranks for a given speaker that can be obtained with probability \( P(R) \). The expected rank is equal to:

\[
E(R) = \sum_{r=1}^{N_{\text{spk}}} R \cdot P(R).
\]  

(8)

To obtain the chance-level rank, we set \( P(R) = \frac{1}{N_{\text{spk}}} \). Hence

\[
E(R) = \frac{1}{N_{\text{spk}}} \sum_{r=1}^{N_{\text{spk}}} R = \frac{1}{N_{\text{spk}}} N_{\text{spk}}(N_{\text{spk}} + 1) \cdot \frac{2}{2} = \frac{N_{\text{spk}} + 1}{2}.
\]  

(9)

When the rank is normalized, we divide the chance-level rank by \( N_{\text{spk}} \) to obtain the normalized chance-level rank

\[
\frac{N_{\text{spk}} + 1}{2N_{\text{spk}}} \approx 0.5.
\]  

(10)

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**REFERENCES**


