A study of bias mitigation strategies for speaker recognition

Raghuveer Peri *, Krishna Somandepalli, Shrikanth Narayanan

Department of Electrical and Computer Engineering, University of Southern California, Los Angeles, CA, USA

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A B S T R A C T

Speaker recognition is increasingly used in several everyday applications including smart speakers, customer care centers and other speech-driven analytics. It is crucial to accurately evaluate and mitigate biases present in machine learning (ML) based speech technologies, such as speaker recognition, to ensure their inclusive adoption. ML fairness studies with respect to various demographic factors in modern speaker recognition systems are lagging compared to other human-centered applications such as face recognition. Existing studies on fairness in speaker recognition systems are largely limited to evaluating biases at specific operating points of the systems, which can lead to false expectations of fairness. Moreover, there are only a handful of bias mitigation strategies developed for speaker recognition systems. In this paper, we systematically evaluate the biases present in speaker recognition systems with respect to gender across a range of system operating points. We also propose adversarial and multi-task learning techniques to improve the fairness of these systems. We show through quantitative and qualitative evaluations that the proposed methods improve the fairness of ASV systems over baseline methods trained using data balancing techniques. We also present a fairness-utility trade-off analysis to jointly examine fairness and the overall system performance. We show that although systems trained using adversarial techniques improve fairness, they are prone to reduced utility. On the other hand, multi-task methods can improve the fairness while retaining the utility. These findings can inform the choice of bias mitigation strategies in the field of speaker recognition.

1. Introduction

Consider a home security system that authenticates the homeowner based on their voice — what if it works reliably only for individuals from certain demographic groups? “What is the practical applicability of such a system?”, “Is this system fair?”, “How do we identify biases in this system?”, and “How might we mitigate these biases?”. Such questions are being addressed at a rapid pace in technology domains such as computer vision and natural language understanding that primarily rely on machine learning (ML) algorithms — leading to the emergence of ML fairness as a field of study in its own right (Barocas et al., 2019). In the context of speech technologies, ML fairness studies are mostly limited to applications such as speech-to-text conversion (Koenecke et al., 2020). Few studies have considered ML fairness for speaker recognition which is a key component in applications such as personalized speech technologies and voice-based biometric authentication.

Speaker recognition is the task of identifying a person based on their voice. Automatic speaker verification (ASV), which is a specific application of speaker recognition, refers to the task of authenticating users based on their voice characteristics. It has found widespread adoption in smart home appliances (e.g., Alexa) (Lisa Eadicicco, 2017), voice authentication in airports (Cornacchia et al., 2020) and, as a biometric system in customer service centers and banks (Derek du Preez, 2013; James Griffiths, 2017). With the

* Corresponding author.
E-mail addresses: rperi@usc.edu (R. Peri), somandep@usc.edu (K. Somandepalli), shri@ee.usc.edu (S. Narayanan).

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improvement of user convenience, i.e., they value seamless verification of impostors. Techniques help mitigate these biases, and improve the fairness of speaker recognition systems. We present experimental findings indicating no existing related work using the corresponding technique to improve fairness.

We propose to employ adversarial (AT, UAI-AT) and multi-task (MTL, UAI-MTL) techniques to improve the fairness of ASV systems. There is limited research in tackling biases in these systems compared to non-speech domains notably in methods for improving fairness of ASV systems. We examine whether adversarial or multi-task learning techniques help mitigate these biases, and improve the fairness of speaker recognition systems. We present experimental findings that demonstrate the conditions under which fairness can be improved, and have made the related code and model information publicly available for the benefit of the research community.¹

Generally, ASV applications have different performance goals depending on the use case. For example, security applications impose strict restrictions on the proportion of impostors² they erroneously admit. On the other hand, smart home applications value user convenience, i.e., they value seamless verification of genuine users at the expense of tolerating more impostor cases. Thus, it is crucial to consider biases that arise in different ASV applications. While tremendous strides are being made in evaluating and improving fairness in applied ML (Barocas et al., 2019), bias mitigation studies for ASV are limited (Fenu et al., 2020b; Shen et al., 2022). In particular, the most recent bias evaluation frameworks for ASV are restricted to specific operating points of systems (Toussaint and Ding, 2021; Fenu et al., 2020a), limiting their scope. Differences in the equal error rate (EER) of an ASV system between different demographic population groups is commonly used as a proxy for the biases present (Fenu et al., 2020a; Shen et al., 2022). EER is the error of the system where the rate of accepting impostors is equal to the rate of rejecting genuine users. Fairness evaluation using differences in EER do not generalize to other use-cases because it only examines a specific operating point of the system. Generalization in the fairness claims of the systems requires a thorough evaluation of biases at several system operating points. In addition, utility of ASV systems, which is the overall performance (not considering any specific demographic group) is an important consideration in the practical applicability of bias mitigation strategies. An ideal mitigation strategy is expected to reduce performance differences between the different demographic groups, with minimal degradation of the system's utility.

Some bias mitigation strategies in ML involve training with class-balanced data (Serna et al., 2021; Zhang and Sang, 2020; Zhao et al., 2018). For ASV, data balancing was studied with respect to age and gender (Fenu et al., 2020b). However, it is not evident if such techniques are the most suitable to induce fairness. For example, in computer vision, data balancing was shown to be insufficient to mitigate biases (e.g., Wang et al., 2019). Another class of techniques to improve fairness developed constraints to tackle biases during training (Zemel et al., 2013; Zafar et al., 2017). When demographic information (e.g., gender, age) is available, it can be used in an adversarial training (AT) setup to learn speaker embeddings (compact speech representations that capture information about speaker's identity) that are fair with respect to the demographic attributes (Li et al., 2021). Adversarial methods for ASV typically train encoders to learn speaker-discriminative embeddings while stripping them of demographic information (Noé et al., 2020). However, these demographic variables are often components of a person's identity (Hassan et al., 2021) and can help improve ASV performance (Luu et al., 2020). For example, it is typically easier to reject an impostor verification claim, when the impostor's gender is different from that of the target speaker. Removing gender-related information from speaker embeddings in this case worsens ASV performance. It may be beneficial to develop ASV systems that perform equally well for people belonging to different demographic groups, despite the speaker embeddings retaining information of the demographic attributes. For this purpose, a multi-task learning (MTL) strategy can be employed to simultaneously predict factors related to speaker identity such as gender, age etc (Luu et al., 2020). The various bias mitigation strategies we study for ASV are summarized in Table 1, alongside some exemplar studies in automatic speech recognition (ASR), and other ML domains. In a recent work (Peri et al., 2020b), we showed that adapting unsupervised adversarial invariance (UAI) (Jaiswal et al., 2018) — an adversarial method proposed for computer vision tasks — for speaker representation learning makes the ASV system robust to adverse acoustic conditions. We extend the UAI method using adversarial and multi-task techniques for bias mitigation in ASV systems. In addition to extensive fairness analyses, we jointly examine the overall performance of the ASV system. This is referred to as fairness-utility trade-off.

¹ Code and information about pre-trained models can be found in https://github.com/rperi/trustworthy-asv-fairness.
² A person impersonating another to maliciously gain access to a biometric system.
Our specific contributions and findings are summarized below:

### Summary of contributions
- We propose novel adversarial and multi-task training methods to improve the fairness of ASV systems. As shown in Table 1, adversarial and multi-task techniques for bias mitigation in ASV systems are limited or non-existent. We compare the proposed methods against baselines that rely on data balancing, using quantitative and qualitative evaluations.
- We systematically evaluate biases present in ASV systems at multiple operating points. Current work in this field is mostly focused on a single operating point, which can lead to an incomplete evaluation of fairness. Even when evaluations are done at multiple operating points, different thresholds are assumed for the different demographic groups which does not accurately reflect the application of these technologies in practice. To this end, we adopt the fairness discrepancy rate metric de Freitas Pereira and Marcel (2021) to measure the fairness of ASV systems under different system operating conditions.
- In addition to fairness evaluations, we also consider the utility, which is the overall system performance, using standard performance metrics such as EER. Joint considerations of fairness and utility can help inform the choice of bias mitigation techniques.

### Summary of findings
- We show that the fairness of baseline ASV systems (trained using data balancing) with respect to gender varies with the operating point of interest. Our experiments show increased bias of the baseline methods as the system operation moves to regions with fewer instances of incorrectly rejecting genuine users. We demonstrate that, compared with the baseline systems, the fairness of the proposed adversarial and multi-task methods have minimal dependence on the operating point.
- We demonstrate using qualitative visualizations and quantitative metrics that the proposed techniques are able to mitigate biases to a large extent compared to the baseline systems based on data balancing. We further show that this observation holds true across a range of different operating conditions.
- We observe that the adversarial technique improves fairness but suffers with reduced utility. In contrast, the multi-task technique is able to improve fairness while retaining the overall system utility. These findings can inform choosing appropriate bias mitigation strategies, while carefully considering the target use-case of the speaker recognition systems.

The rest of the paper is organized as follows. In Section 2, we provide background of existing work related to fairness in ASV. Section 3 details the methodology used to induce fairness in ASV systems, followed by a description of the metrics we use to evaluate these methods in Section 4. We provide a brief description of the datasets used to build and evaluate our models in Section 5. Section 6 outlines the baselines and experiments designed to investigate the biases in the developed ASV systems (including ablation studies). This is followed by the corresponding results and discussions in Section 7. Finally, we conclude the paper in Section 8, where we summarize our findings, and provide avenues for potential future research.

2. Background

In this section, we examine related work on fairness in ASV systems, with regard to other ML applications. Specifically, we discuss related-work of two key aspects relevant to this paper: (1) Evaluation of biases in ASV systems (2) Bias mitigation strategies, which include adversarial and multi-task methodologies.

Fairness studies in applied ML have become prolific. A few prominent examples include facial analysis (Buolamwini and Gebru, 2018; Klare et al., 2012; Robinson et al., 2020; Grother et al., 2019; Howard and Borenstein, 2018; Beveridge et al., 2009; Howard et al., 2019; Ryu et al., 2017), natural language understanding (Sap et al., 2019; Bolukbasi et al., 2016; Park et al., 2018; Díaz et al., 2018; Dixon et al., 2018), affect recognition (Xu et al., 2020; Stoychev and Gunes, 2022; Gorrostieta et al., 2019), criminal justice (Green, 2018; Chouldechova, 2017; Wadsworth et al., 2018; Mishler et al., 2021), and health care (Hamon et al., 2021; Suriyakumar et al., 2021). In speech technology research, fairness studies are mostly limited to automatic speech recognition (Liu et al., 2021b; Sari et al., 2021; Liu et al., 2021a; Garnerin et al., 2021). The field of biometrics is perhaps the most relevant for speaker verification. As noted by Drozdowski et al. (2020), most bias detection and mitigation works in biometrics focus on face recognition (Grother et al., 2019; Beveridge et al., 2009; Ryu et al., 2017; Klare et al., 2012), and some on fingerprint matching (Galbally et al., 2018; Preciozzi et al., 2020). Fairness in voice-based biometrics remains an underexplored field with only a handful of works (Fenu et al., 2020b; Toussaint and Ding, 2021; Fenu et al., 2021; Shen et al., 2022).

2.1. Evaluating biases in ASV systems

As shown in Fig. 1, ASV involves making a binary accept/reject decision by comparing the similarity of the enrollment and test speech utterance based on a pre-determined threshold. The threshold is tailored to suit the end application: a lower threshold for
Fig. 1. Block diagram of a typical deep-learning based ASV system. Pre-trained speaker embedding models are used to represent the enrollment speech (from a pre-enrolled speaker) and the test speech (uttered by the user who is attempting to be verified). Similarity between the representations is computed and a threshold is applied on the similarity scores. The verification claim is accepted if the similarity score exceeds the threshold. The inset figure shows a histogram of the similarity scores of a typical ASV system. Genuine verification pairs with scores smaller than the threshold contribute to false rejects, while impostor verification scores greater than the threshold contribute to false accepts. The threshold determines the operating point, and can be chosen suitable to the use-case.

high-convenience applications and a higher threshold for high-security applications. As a result, bias evaluation methods that rely on specific operating points can lead to incomplete conclusions about system fairness. Owing to the recent challenges organized by NIST (Sadjadi et al., 2017, 2019), there is an increased focus on improving ASV performance across languages (Torres-Carrasquillo et al., 2017; Lee et al., 2019). Multi-lingual analyses were added in the latest VoxSRC challenge (Brown et al., 2022). However, related performance evaluations used only a specific operating point characterized by the EER metric. Some studies have examined differences in the distribution of speaker verification scores between demographic groups (Stoll, 2011; Si et al., 2021). However, it is unclear how downstream system decisions are affected by such upstream studies. In a more recent work, fairness of ASV systems with respect to age and gender was explored (Fenu et al., 2020a). However, the fairness evaluation metric was again limited to the disparity in EER between demographic groups. Toussaint and Ding (2021) proposed a fairness evaluation framework for ASV systems using a minimum detection cost function, which only considers a single operating point determined by a threshold from speaker verification scores. The detection error trade-off (DET) curves proposed in Toussaint and Ding (2021) rely on demographic-specific thresholds which is not practical for deployment as inferring a user’s background which is private, is sensitive and complicated. Fenu et al. (2021) performed fairness evaluations using several different definitions of fairness at multiple operating points with a focus on data balancing strategies to mitigate biases. Similarly, in this work, we adopt the fairness discrepancy rate (FaDR) metric that was recently proposed for biometric systems (de Freitas Pereira and Marcel, 2021). FaDR estimates at different operating points can be used to systematically analyze the fairness of the proposed methods. A detailed explanation of the FaDR metric can be found in Section 4.

Fairness-Utility trade-off: ASV systems can be biased to perform better for certain demographic populations (Fenu et al., 2020a). Although reliance on demographic information can potentially improve ASV performance, it can lead to unfair systems that discriminate against certain demographic groups. Thus, there is a trade-off between fairness and utility. Such trade-offs are studied extensively in the broader literature on Fair-ML (Zhao and Gordon, 2019; Calders et al., 2009; Haas, 2020; Du et al., 2020). For example, Zhao and Gordon (2019) have shown that adversarial training to improve fairness reduce the overall system utility. However, empirical studies demonstrating such trade-offs between fairness and utility in ASV systems are limited (Fenu et al., 2021). In this work, we study how our proposed techniques perform in improving fairness, while also evaluating their utility using standard metrics.

2.2. Mitigating biases in ASV systems

Prior work has demonstrated differences in the performance of ASV systems across gender groups (Reynolds et al., 2000). This led to the development of gender-specific models that were used in combination with a gender classification module in ASV (Bimbot et al., 2004; Kanervisto et al., 2017). This was the case even in popular i-vector-based ASV models (Dehak et al., 2011). However, such a methodology of training separate models for each demographic group needs the demographic group label (either self-reported by the speaker or predicted by a model) at the time of inference. This information may not always be available, or possible to infer. In addition, such methods can further perpetuate biases and undermine certain privacy criteria by requiring the systems to infer demographic attributes. Therefore, for practical purposes, it is desirable to develop unified demographic-agnostic ASV models. Most recent deep learning-based approaches train a unified model agnostic to the demographic groups, while trying to ensure substantial representation from each group in the training data (Chung et al., 2018). However, such systems can still be prone to bias issues because they are not explicitly trained to induce fairness.

In fair-ML literature, algorithms to improve fairness or mitigate biases fall into one of the three categories: pre-processing, post-processing and in-processing (Mehrabi et al., 2019). A common pre-processing method to develop fair models is to train them using
data that are balanced with respect to the various potential sources of bias (Zhang and Sang, 2020). This approach has been explored in ASV systems, where data from individuals that are balanced with respect to gender, language, and age are used to train models to improve fairness (Fenu et al., 2020b). Post-processing techniques are used when only access to a pre-trained model is available and it is not practical to train models using one’s data (Bellamy et al., 2018). Such techniques are commonly employed in closed-set classification tasks. It is not straightforward to generalize them to a verification setup like ASV. In-processing techniques involve explicitly inducing fairness into the model during training by introducing fairness constraints (Berk et al., 2017). A common method is adversarial techniques that use demographic information during training to learn de-biased representations (Zhang et al., 2018). When demographic labels are available, they can also be used in a multi-task fashion to reduce the performance disparity between groups (Xu et al., 2020).

Adversarial Training and Multi-task Learning: In adversarial training (AT) methodology, the labels used to learn the embeddings are devoid of demographic information. Since the embeddings contain very little demographic information, it is likely that the systems will use discriminative signals for the primary prediction task and rely less on demographic attributes, making the systems fairer (Zhang et al., 2018). AT has shown promise in developing unbiased classification models (Edwards and Storkey, 2015; Zhang et al., 2018). Some studies in face recognition (e.g., Morales et al., 2020) have shown the efficacy of AT to improve fairness. However, it is not clear whether these benefits translate to ASV systems. Language-invariant speaker embeddings for ASV have been developed using adversarial methods (Bhattacharya et al., 2019). However, the evaluations were limited to a single operating point characterized by EER. Noé et al. (2020) employed AT to develop speaker embeddings devoid of certain sensitive attributes. However, their goal was preserving privacy and not improving fairness, which at times can be at odds during system development.

To the best of our knowledge, such techniques have not been used for developing fair ASV systems, and we explore that direction in this work.

Demographic labels could also be used in a multitask fashion with label prediction as a secondary task to learn demographic-aware embeddings. This is particularly useful for recognition tasks such as face/speaker identity, where the demographic attributes form part of the person’s identity. In such cases, instead of stripping the demographic information, one can train models to ensure that the performance of the systems is similar across demographic groups. Xu et al. (2020) proposed providing demographic information to a facial expression recognition model to improve fairness. However, these observations were based on a classification task, different from a verification setup. In biometric settings (which is closer to our target ASV task), multi-task training methods can be used to add demographic information to the general-purpose representations. Luu et al. (2020) showed that demographic information can be used in a multi-task setup to improve utility of ASV systems. However, the fairness of MTL systems has not been studied. In a more recent work, Shen et al. (2022) showed gender-specific adaptation of encoders to extract gender-specific embeddings to improve ASV fairness. They also showed that it can improve not only the fairness but also the overall system utility. However, fairness evaluations were limited to differences in EER between the genders. We intend to investigate whether using MTL to train demographic-aware speaker embeddings improves the ASV utility in addition to reducing the differences in performance between different demographic groups present in a dataset.

3. Methods

We develop methods to transform existing speaker embeddings to another representation space with the goal of minimizing biases with respect to demographic groups in ASV systems. This is achieved by training models using demographic labels in addition to the speaker identity labels. We explore adversarial and multi-task techniques to train the embedding models to improve the fairness of pre-trained speaker embeddings. We employ the unsupervised adversarial invariance (UAI) framework, which was originally proposed in Jaiswal et al. (2018). We had adapted this approach in our previous work to disentangle speaker factors from nuisance factors unrelated to the speaker’s identity present in x-vectors (Peri et al., 2020a). However, as noted by Jaiswal et al. (2019), the UAI technique cannot be directly used to induce invariance to demographic factors in an unsupervised fashion, and demographic labels are needed to induce invariance using adversarial techniques. Therefore, we propose to use the adversarial extension of the UAI technique developed by Jaiswal et al. (2019). In addition, we also propose a novel multi-task extension to the UAI framework. Fig. 2 shows the schematic diagram of the proposed method. The techniques including UAI and its adversarial and multi-task extensions are explained in detail below.

3.1. Unsupervised adversarial invariance (UAI)

The central idea behind this technique is to project the input speaker representations into a split representation consisting of two embeddings, referred to as e1 and e2 in Fig. 2. While e1 is trained with the objective of capturing speaker-specific information, e2 is trained to capture all other nuisance factors. This is achieved by training two branches in an adversarial fashion.

\[
L_{prim} = \alpha L_{pred}(s, \hat{s}) + \beta L_{recon}(x, \hat{x})
\]

\[
L_{sec} = L_{dis1}(e_1, \hat{e}_1) + L_{dis2}(e_1, \hat{e}_1)
\]

\[
\min_{\theta_{prim}} \max_{\theta_{sec}} L_{prim} + \gamma L_{sec}
\]

where \(\theta_{prim} = \theta_s \cup \theta_d \cup \theta_p\), \(\theta_{sec} = \phi_{dis1} \cup \phi_{dis2}\)

\[
\text{Fig. 2. While e1 is trained with the objective of capturing speaker-specific information, e2 is trained to capture all other nuisance factors. This is achieved by training two branches in an adversarial fashion.}
\]

\[
\text{1)}
\]

\[
\text{2)}
\]

\[
\text{3)}
\]
The goal of one branch, called **primary** branch (consisting of the encoder, predictor and decoder shown in green bounding boxes in Fig. 2), is to predict speakers using $\mathbf{e}_1$ as input (using the **predictor** module) and reconstruct the x-vectors using $\mathbf{e}_2$ and a randomly perturbed version of $\mathbf{e}_1$ as input (using the **decoder** module). The random perturbation ensures that the network learns to treat $\mathbf{e}_1$ as an unreliable source of information for the reconstruction task, hence forcing $\mathbf{e}_1$ to not contain information about factors other than the speaker. The perturbation of $\mathbf{e}_1$ is modeled as a dropout module that randomly removes some dimensions from $\mathbf{e}_1$ to create a noisy version denoted by $\mathbf{e}_1'$. The primary branch produces the loss term shown in Eq. (1), where $L_{\text{pred}}$ is modeled as categorical cross-entropy loss to predict speakers, and $L_{\text{recon}}$ is modeled as mean squared error (MSE) reconstruction loss of the decoder. The terms $\Theta_e, \Theta_p, \Theta_d$ denote the network parameters of the encoder, decoder and predictor respectively as shown in Fig. 2. The speaker prediction task forces $\mathbf{e}_1$ to capture speaker-related information, while the reconstruction task ensures that $\mathbf{e}_2$ captures information related to all factors.

The other branch, called the **secondary** branch (consisting of the disentanglers shown in red bounding boxes in Fig. 2), is trained to minimize the mutual information between $\mathbf{e}_1$ and $\mathbf{e}_2$. This is achieved in the **disentangler** module consisting of two networks that predict $\mathbf{e}_1$ from $\mathbf{e}_2$ and vice-versa. The secondary branch produces the loss term given in Eq. (2) which is the sum of the two disentanglement losses, each of which is modeled as MSE loss. The terms $\Phi_{\text{dis1}}, \Phi_{\text{dis2}}$ denote the network parameters of the disentangler modules shown in Fig. 2. The UAI model is trained with a minimax objective shown in Eq. (3) by alternating between the primary and secondary branch updates according to a fixed schedule. The parameters $\alpha, \beta, \gamma$ control the contribution of the prediction, reconstruction and the disentanglement loss terms respectively. We would like to point out that the unsupervised disentanglement approach of UAI shares some methodological commonalities with a few existing works such as Qian et al. (2020) and Bhati et al. (2020). However, there are certain key differences. While (Qian et al., 2020) deals with specific factors of variability such as timbre, rhythm etc., UAI is able to separate out the speaker factors from multiple nuisance factors. Though (Bhati et al., 2020) perform information separation using two branches similar to UAI, there is no explicit mechanism to prevent leakage of information across branches as in the UAI technique. Detailed explanation of the method to disentangle speaker representations can be found in Peri et al. (2020b).

As reported in our previous work (Peri et al., 2020a), a characteristic of this technique is that it disentangles the speaker identity from nuisance factors, which are all the factors unrelated to the speaker's identity (Peri et al., 2020a), such as acoustic noise, reverberation etc. Jaiswal et al. (2019) proposed an extension to the UAI technique, called unified adversarial invariance, which uses the demographic labels to induce invariance to those attributes. We explore this framework, in addition to a multi-task extension to improve fairness of ASV systems.

### 3.2. Adversarial and multi-task extensions of UAI: UAI-AT and UAI-MTL

UAI by itself cannot provide invariance to demographic factors. Therefore, Jaiswal et al. (2019) extended the UAI framework to include demographic labels during training. In particular, they introduced a **discriminator** that is used to predict demographic
labels. In the formulation proposed in Jaiswal et al. (2019), this discriminator (shown in yellow bounding box in Fig. 2) is trained in an adversarial fashion along with the disentangler of the UAI.

\[
\min_{\theta \_\text{prim}} \max_{\theta \_\text{sec}} \; L_{\text{prim}} + \gamma L_{\text{sec}} + \delta L_{\text{bias}}(b, \hat{b})
\]

\[ \text{UAI-AT: } \theta_{\text{prim}} = \theta_s \cup \theta_d \cup \theta_p, \; \Phi_{\text{sec}} = \Phi_{\text{dis}1} \cup \Phi_{\text{dis}2} \cup \theta_b \]

\[ \text{UAI-MTL: } \theta_{\text{prim}} = \theta_s \cup \theta_d \cup \theta_p \cup \theta_b, \; \Phi_{\text{sec}} = \Phi_{\text{dis}1} \cup \Phi_{\text{dis}2} \]

Eq. (4) shows the training objective that includes the discriminator loss denoted by $\delta$, which is modeled as cross-entropy loss with respect to language, they do not evaluate the systems using fairness metrics. Moreover, different from the previous works, our method has an additional unsupervised information separation stage. The discriminator loss is modeled as categorical cross-entropy loss between the true and predicted demographic labels denoted as $b$ and $\hat{b}$ respectively. We denote the method of adversarially training the discriminator along with UAI as UAI-AT throughout the rest of the paper. The term corresponding to UAI-AT in Eq. (4) shows how the discriminator (with set of trainable parameters denoted by $\theta_b$ being part of the secondary branch) is trained adversarially with the predictor. This ensures that the learned embeddings $e_i$ do not retain demographic information, thereby achieving the desired invariance. Though a previous work (Bhattacharya et al., 2019) has used an adversarial disentanglement approach to reduce biases with respect to language, they do not evaluate the systems using fairness metrics. Moreover, different from the previous works, our method has an additional unsupervised information separation stage. The discriminator loss is modeled as categorical cross-entropy loss between the true and predicted demographic labels.

On the other hand, it is not evident if adversarial training to induce invariance to demographic factors is necessary to learn fair representations. Given the demographic labels, they can be used to train the discriminator in a multi-task (as opposed to adversarial) fashion. We call these demographic-aware speaker representations, and this method is denoted as UAI-MTL in the rest of the paper. The term corresponding to UAI-MTL in Eq. (4) shows how the discriminator parameters (being part of the primary branch) are trained in a multi-task fashion with the predictor. The objective is to learn a representation that captures speaker identity information while retaining the demographic attribute information. In both the UAI-AT and UAI-MTL methods, the parameter $\delta$ controls the contribution of the discriminator loss to the overall loss term.

4. Metrics

In this section, we provide details of the metrics that we use to evaluate the fairness and utility of ASV systems. A brief description of each metric is also provided in Table 2 for a quick reference.

4.1. Utility: Equal error rate (EER)

EER refers to a particular operating point of the system where the FAR equals FRR. This metric is commonly used to evaluate the utility of ASV systems. Lower values of EER signify better system utility. We chose EER over the minimum detection cost function (minDCF), which is another commonly used evaluation metric, as minDCF requires specifying parameters such as the relative costs of the detection errors and the target speaker prior probability, which imply a particular application (Van Leeuwen and Brümmer, 2007). We wanted to avoid introducing additional variability arising due to the different parameters. Note that we only use EER to measure utility and not to evaluate fairness.

4.2. Fairness: Fairness discrepancy rate (FaDR)

As discussed in Section 2, a reasonable goal of fairness in ASV systems is to ensure that the performance differences between demographic groups is small across a range of different operating points. Algorithms that are fair only at certain operating points can result in a false sense of fairness, and can be detrimental when used to design systems with real-world applications.

A straightforward way to analyze the fairness of biometric systems is to use the disparity in EER between the demographic groups (termed as differential outcomes by Howard et al., 2019) as an indication of the fairness (Fenu et al., 2020b; Shen et al., 2022). However, this approach assumes that each demographic group has its own threshold on the verification scores. This can lead to false notions of fairness, because in most real-world systems a single threshold is used for verification irrespective of the demographic group (de Freitas Pereira and Marcel, 2021). In order to overcome this limitation, Periera and Mercel (de Freitas Pereira and Marcel, 2021) propose a metric called fairness discrepancy rate (FaDR) to account for FARs and FRRs in biometric systems.

They propose to evaluate fairness at multiple thresholds that can be chosen agnostic of the demographic groups. A recently shared draft by NIST3 highlights the importance of choosing such metrics for evaluating the fairness in biometrics. We employ this metric to evaluate the fairness of our models.

\[
\text{FaDR}(\tau) = 1 - \alpha A(\tau) + (1 - \alpha) B(\tau)
\]

\[
A(\tau) = |FAR^{b}(\tau) - FAR^{\hat{b}}(\tau)|, \quad B(\tau) = |FRR^{b}(\tau) - FRR^{\hat{b}}(\tau)|
\]

Intuitively, FaDR computes the weighted combination of absolute differences in FARs and FRRs between demographic groups. The threshold $\tau$ is applied on demographic-agnostic verification trials to compute the demographic-agnostic FAR (corresponding to the zero-effort score distribution used by Periera and Mercel de Freitas Pereira and Marcel, 2021), which characterizes a particular

3 https://pages.nist.gov/frvt/reports/demographics/nistir_8429.pdf
operating point of the system. The fairness of a system can be measured at different values of the threshold \( \tau \) corresponding to different operating points. Assuming two demographic groups are of interest, at a given threshold \( \tau \), FaDR\(^4\) is defined in Eq. (5) where \( FAR_{\tau}(\gamma) \) and \( FRR_{\tau}(\gamma) \) refer to the FAR and FRR, when the threshold is applied on the similarity scores of verification pairs consisting only of speakers belonging to demographic group \( g_1 \) (similarly for demographic group \( g_2 \)). To contextualize it with the terminology used by Grother et al. (2019), this can be viewed as a weighted combination of FA and FR differentials, with the error discrepancy weight given by \( \omega \) (0 <= \( \omega \) <= 1).

4.2.1. Note on error discrepancy weight (\( \omega \))

FaDR can be computed by weighing the discrepancy between the demographic groups in 2 different types of errors, FAR and FRR. The error discrepancy weight, \( \omega \) in Eq. (5), can be used to determine the importance of the different types of errors. \( \omega = 1.0 \) corresponds to the case where the differences between the demographic groups are evaluated only using their FARs. Similarly, \( \omega = 0.0 \) corresponds to considering the differences only in the FRRs between demographic groups. \( \omega = 0.5 \) reflects the condition that discrepancy between the demographic groups in FAs and FRs are equally important. Intuitively, it can be used to weigh the relative importance of the discrepancy in FAR and FRR between the demographic groups. For example, evaluating FaDR at high values of \( \omega \) could be useful in applications such as in border control where FAs are critical (de Freitas Pereira and Marcel, 2021). A larger emphasis can be given to reducing demographic disparity in accepting impostor verification pairs. Similarly, smaller values of \( \omega \) can be used to evaluate the fairness in applications such as in smart speakers where considering FRRs that can degrade the user experience is more important.

4.3. Fairness: Area under the FaDR-FAR curve (auFaDR-FAR)

FaDR can be computed at various operating points of an ASV system by varying the threshold on verification similarity scores. These thresholds are applied on demographic-agnostic verification scores to compute demographic-agnostic FARs. Therefore, we can obtain a curve showing the FaDR of the system at various demographic-agnostic FAR values, and this curve can be used to compare the fairness of different systems. Furthermore, Pereira and Mercel (de Freitas Pereira and Marcel, 2021) propose the use of area under the FaDR-FAR (auFaDR-FAR) curve as an objective summary of the fairness of a system for various conditions. We use this as the primary metric for evaluation because it summarizes the fairness of systems at the operating points of interest.

5. Dataset

In this section, we provide details of the datasets used for training and evaluating our models. We employed different subsets of the Mozilla Common Voice (MCV) dataset (Ardila et al., 2020) in our experiments. In addition, we also used a subset of the Voxceleb1 dataset as an out-of-domain evaluation set. The MCV corpus consists of crowd-sourced audio recordings of read speech collected from around the world in multiple languages. We also used the Voxceleb1 dataset (Nagrani et al., 2017) as an external corpus (different from the MCV corpus) to evaluate the generalizability of the described methods on out-of-domain data. It consists of in-the-wild recordings of celebrity interviews with speaker identity labels. Unlike in the MCV corpus, the gender labels in Voxceleb1 were not self-reported but obtained from Wikipedia. The subsets of these corpora we use in our experiments are described below, and their statistics are provided in Table 3.

5.1. Training

We use the following datasets to train the speaker embedding transformation model using the methods described in Section 3. These datasets consist of speech samples with speaker identity labels and demographic labels such as gender and language. 

\[^{4}\text{This definition is a special case of FaDR when only two demographic groups are present. A more general definition can be found in de Freitas Pereira and Marcel (2021).}\]
To overcome these limitations in the future, we restrict our analysis to binary gender categories due to the limitation imposed by the availability of labels in existing speech datasets (Garnerin et al., 2021), and hope with no overlap between speakers. Voxceleb-H is an out-domain evaluation dataset, and unlike all the other datasets, is not collected from the MCV corpus.

In Section 3, we described methods to transform pre-trained speaker embeddings to induce fairness. In this section, we describe the experiments designed to evaluate the fairness and utility of the proposed UAI-AT and UAI-MTL methods, by comparing them against suitable baselines. In addition, we describe the ablation studies we performed to investigate the importance of the different modules used in our methods.

### 5.2. Evaluation

The following datasets are used to evaluate the transformed speaker embeddings for their utility and fairness in ASV.

- **eval-dev**: We use this data to create development set verification pairs to fine-tune hyperparameters of our models, such as the bias weight in Eq. (4). The speakers in this subset are unseen during training (speakers not present in any of the subsets described in Section 5.1). Tuning hyperparameters on this subset using metrics useful for verification allows us to build models that are better suited for the task of speaker verification. Roughly 1.3M verification pairs were created from this data. Evaluations were performed on separate subsets of the pairs corresponding to different genders. For example, to evaluate verification performance on the female demographic group, pairs were created using enrollment and test utterances only from speakers belonging to the female demographic group.

- **eval-test**: Similar to eval-dev data described above, this contains recordings from speakers not present in any of the above datasets. Particularly, there is no speaker overlap with the eval-dev dataset. Verification pairs from this data are used to evaluate models in terms of both fairness and utility. This dataset was used as held-out data to evaluate only the best models (after hyperparameter tuning). More than 1M verification pairs were created from this data.

- **voxceleb-H**: Following Toussaint and Ding (2021), we performed evaluations on the voxceleb-H split (https://www.robots.ox.ac.uk/~vgg/data/voxceleb/meta/list_test_hard2.txt). It is a subset of Voxceleb1 containing 1190 speakers, and 500K verification trials consisting of same gender and same nationality pairs. Different from the MCV corpus which is mostly read speech, the Voxceleb1 dataset consists of recordings from celebrity interviews in an unconstrained setting. This dataset facilitates fairness evaluations of ASV systems in more relaxed settings consisting of spontaneous speech. We utilize all the pairs from this trial list because they are all same-gender verifications.

| #spk. | xvector-train-U | xvector-train-B | embed-train | embed-val | eval-dev | eval-test | voxceleb-H |
|-------|-----------------|-----------------|-------------|-----------|----------|----------|------------|
| M     | 124,179         | 101,527         | 117,918     | 30,205    | 633,126  | 528,666  | 324,206    |
| F     | 86,332          | 81,104          | 51,016      | 12,989    | 721,370  | 545,103  | 226,690    |

In Table 3, the following datasets are used to train and evaluate speaker embedding models. xvector-train-U is not balanced. embed-train and embed-val (used to train proposed models) have different utterances from the same set of speakers to facilitate evaluating speaker classification performance during embedding training. eval-dev and eval-test (used to evaluate ASV utility and fairness) have speech utterances with no overlap between speakers. Voxceleb-H is an out-domain evaluation dataset, and unlike all the other datasets, is not collected from the MCV corpus.

| #spk. | xvector-train-U | xvector-train-B | embed-train | embed-val | eval-dev | eval-test | voxceleb-H |
|-------|-----------------|-----------------|-------------|-----------|----------|----------|------------|
| M     | 124,179         | 101,527         | 117,918     | 30,205    | 633,126  | 528,666  | 324,206    |
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The speakers in this subset are unseen during training (speakers not present in any of the subsets described in Section 5.1). Tuning hyperparameters on this subset using metrics useful for verification allows us to build models that are better suited for the task of speaker verification. Roughly 1.3M verification pairs were created from this data. Evaluations were performed on separate subsets of the pairs corresponding to different genders. For example, to evaluate verification performance on the female demographic group, pairs were created using enrollment and test utterances only from speakers belonging to the female demographic group.

### 6. Experiments

In Section 3, we described methods to transform pre-trained speaker embeddings to induce fairness. In this section, we describe the experiments designed to evaluate the fairness and utility of the proposed UAI-AT and UAI-MTL methods, by comparing them against suitable baselines. In addition, we describe the ablation studies we performed to investigate the importance of the different modules used in our methods.

**Setup**: Our method consists of training an embedding transformation model using speaker identity and demographic labels in a closed-set classification setup. For this paper, we restrict our analyses to gender as the demographic attribute for which fairness

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5 We use the term gender to refer to the self-reported gender in the datasets, except for Voxceleb, where the labels were obtained from Wikipedia. We restrict our analysis to binary gender categories due to the limitation imposed by the availability of labels in existing speech datasets (Garnerin et al., 2021), and hope to overcome these limitations in the future.
is desired, but the proposed methods can be extended to other demographic attributes (e.g., age) as well. The encoder from the trained speaker representation model is used to extract embeddings, that are then evaluated for fairness and utility in a speaker verification setting. Below we describe the baselines along with the training setup of the proposed methods. We then discuss the evaluation setup and implementation details.

6.1. Baselines

The pre-trained speaker embeddings used as input to our models were chosen from the prior methods developed to improve fairness in ASV systems (Fenu et al., 2020b). We compare our methods against ASV systems developed using these chosen off-the-shelf embeddings as baselines, which allows us to investigate the effectiveness of our proposed methods in improving the fairness of existing speaker embeddings.

- **x-vector-U**: As a weak baseline, we use the pre-trained models\(^6\) that were trained using data not balanced with respect to gender. Specifically, the models were trained using the xvector-train-U dataset described in Section 5. Evaluation on this baseline provides an understanding of the biases present in speaker verification systems trained using unbalanced data. This is particularly important because most existing speaker verification systems rely on speaker embedding models trained on large amounts of data, typically without specific attention to data balancing.

- **x-vector-B**: Data balancing is a common technique used to develop fair ML systems. Fenu et al. (2020b) have employed this strategy to improve fairness of speaker verification systems. This is a stronger baseline against which the proposed UAI-AT and UAI-MTL methods are compared. We use pre-trained models\(^7\) that were trained using the xvector-train-B dataset described in Section 5.

6.2. Proposed methods

We trained models with the following methods using gender labels along with the speaker labels on the embed-train dataset described in Section 5.1. As mentioned before, the embed-train dataset is a subset of the xvector-train-U dataset (Though, in theory we could use the full xvector-train-U dataset, we were able to obtain only a subset due to missing recordings). In contrast with the xvector-train-B dataset, the training data samples are not balanced with respect to the gender labels.\(^8\) The advantage of the proposed methods are that they can leverage all the available data without explicit data balancing.

We used the speaker embeddings referred to as x-vector-B in the previous Section 6.1 as input to our models. The rationale behind using these embeddings was that these were trained using an existing data-balancing technique and have shown to improve fairness (Fenu et al., 2020b). This allowed us to explore the proposed techniques (mentioned below) as a means to further improve the fairness of existing ASV systems that are already trained to reduce biases.

- **UAI-AT**: As described in Section 3.2, the gender labels can be used in addition to the UAI technique, similar to the technique proposed by Jaiswal et al. (2019) to improve fairness. As shown in Table 4, all modules including the discriminator from Fig. 2 were employed. The optimization was implemented as an alternating mini-max game, where the predictor training forces the encoder to retain speaker information, while the discriminator training forces it to strip demographic information. In the minimization step the encoder and the predictor from Fig. 2 were updated while keeping the secondary branch (discriminator and disentanglers) frozen for a few iterations. In the maximization step, the encoder and the secondary branch were updated keeping the primary branch frozen. This way, the encoder was trained to retain speaker identity information while discarding information about the demographic attributes from the intermediate speaker representations. In practice, instead of maximizing the discriminator loss, we minimized the loss between the predictions and a random sampling of the gender labels from the empirical distribution obtained from the training data, similar to the technique used in Jaiswal et al. (2019), Alvi et al. (2018).

- **UAI-MTL**: Different from the adversarial training strategy, here the gender labels were used in a multi-task fashion. Similar to the UAI-AT technique, predictor training forces the encoder to retain speaker information. However, in this case, the discriminator is trained in a multi-task fashion using gender labels to explicitly force the encoder to learn demographic information, producing demographic-aware speaker embeddings. This is achieved by making the discriminator a part of the primary branch, with the secondary branch consisting of only the disentanglers.

6.3. Ablation studies

As discussed in Section 3 and shown in Table 4, the proposed UAI-AT and UAI-MTL techniques use all the modules including the encoder, predictor, decoder, disentanglers and discriminators. We performed ablation studies to better understand the impact of

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\(^6\) https://drive.google.com/drive/folders/1FW7kUbNu2wQpsaZ6PVFEzLg2ZjKbQ7

\(^7\) https://drive.google.com/drive/folders/1sGqO9p7p6VXXY6ovm64kidd7ue5dE

\(^8\) We also performed experiments using our proposed methods trained with gender-balanced data. However, preliminary results demonstrated that the fairness improvements are better when trained without explicit data balancing.
Table 4
Table showing active blocks (corresponding to Fig. 2) used in different embedding transformation techniques. All the techniques use an encoder to reduce the dimensions of the input speaker embeddings and a predictor to classify speakers. The NLDR and UAI techniques do not require a discriminator since they do not use demographic attribute labels to achieve invariance. The MTL and AT techniques do not employ the disentangler module. The UAI-AT and UAI-MTL techniques use discriminator with demographic attribute labels in addition to the disentangler module. The first four rows denote ablation experiments, while the last two correspond to the proposed techniques.

| Module          | Encoder | Predictor | Decoder | Disentangler | Discriminator |
|-----------------|---------|-----------|---------|--------------|---------------|
| NLDR            | ✓       | ✓         |         |              |               |
| UAI             | ✓       | ✓         | ✓       | ✓            |               |
| MTL             | ✓       | ✓         |         | ✓            | ✓             |
| AT              | ✓       | ✓         | ✓       | ✓            | ✓             |
| UAI-AT          | ✓       | ✓         | ✓       | ✓            | ✓             |
| UAI-MTL         | ✓       | ✓         | ✓       | ✓            | ✓             |

Each module on the performance by selectively retaining certain modules. We also considered the scenario where gender labels are not available. In such scenarios, we investigate if fairness can be improved either by UAI or by simple dimensionality reduction using neural networks, which we term non-linear dimensionality reduction (NLDR). This is in contrast to linear dimensionality reduction approaches such as principal component analysis. The modules corresponding to Fig. 2 that are active in these experiments are shown in Table 4.

- **Non-linear dimensionality reduction (NLDR):** We investigate the effect of non-linear transformation of speaker embeddings while retaining speaker identity information without considering the demographic information. This is achieved by training a neural network to transform pre-trained speaker embeddings using only the speaker labels. This helps understand if simple dimensionality reduction techniques can provide benefits in terms of reducing the biases in the systems. We denote this experiment as NLDR, since the model is trained using just the encoder and predictor modules with non-linear activation functions.

- **UAI:** As described in Section 3, the UAI technique was used to improve the robustness of speaker verification systems to nuisance factors such as acoustic noise, reverberation etc., that are not correlated with speaker's identity (Peri et al., 2020b). However, since demographic attributes such as gender and age are related to the speaker's identity, we had observed that this method does not remove these biases from the speaker embeddings (Peri et al., 2020a). We evaluate if such training can improve the fairness without the need for demographic label information. As shown in Table 4, all modules except the discriminator from Fig. 2 were used in training.

- **AT:** We trained models using the encoder, predictor and discriminator in a standard adversarial setting (without disentanglers). Similar to UAI-AT, the speaker classification task of the predictor forces the encoder to learn speaker-related information, while the discriminator training forces the encoder to learn representations stripped of demographic information. The adversarial loss was implemented by training the encoder to minimize predictor loss while maximizing the discriminator loss using alternating minimization and maximization steps. This experiment allowed us to investigate the importance of the disentanglers in the training process.

- **MTL:** Similar to the AT setup described above, we used only the discriminator module along with the encoder and predictor modules. In contrast to AT setup, here we trained the discriminator in a multi-task setting with the predictor. This ensured that the encoder retained the speaker information (due to the predictor), and also the demographic information (due to the discriminator). The results of this experiment can be compared with the UAI-MTL method to evaluate the importance of the disentanglers.

### 6.4. Evaluation setup

We used the encoder from the speaker representation models trained using the techniques mentioned above as the embedding transformation module. Specifically, we transformed the x-vector-B speaker embeddings (explained in Section 6.1) into a new set of speaker representations using the trained encoders. These transformed speaker embeddings produced from the verification evaluation dataset (Section 5.2) were evaluated using the standard ASV setup shown in Fig. 1. We used pre-determined enrollment and test pairs generated from the evaluation data, and compute similarity scores using cosine similarity (inner product of two unit-length vectors). We then applied a threshold on the similarity score to produce an accept or reject decision for each verification trial, and the error rates were computed by aggregating the decisions over all the pairs. To compute fairness metric (FaDR detailed in Section 4), the FARs and FRRs for each demographic group were separately computed using verification trials belonging to that demographic group. For example, to compute the FAR and FRR for the female population, we aggregated the verification trials where both enrollment and test utterances belong to the female gender. Following Pereira and Mercel (de Freitas Pereira and Marcel, 2021), we do not consider cross-gender trials (where enrollment and test utterances belong to different genders), because they tend to produce substantially lower FARs than same-gender trials (Haustamäki et al., 2010). To compute the demographic-agnostic FAR values useful for evaluating the auFaDR-FAR metric described in Section 4, we pooled all the verification trials agnostic to their demographic attributes.
6.4.1. Statistical testing for differences in performance

We used permutation tests to evaluate the statistical significance of our results. In particular, we used random permutations of the verification scores of the x-vector-B baseline and the proposed methods (UAI-AT or UAI-MTL) to generate a distribution of auFaDR-FAR values. The 'true' auFaDR-FPR (without permuting) was compared against this distribution of synthetically generated auFaDR-FAR values to compute the p-value. We used $n = 10^4$ permutations on randomly chosen 100,000 verification trials, with $p < 0.01$ to denote significance. For testing the significance of the differences in %EER, we employed a similar permutation test strategy, but instead used all the verification trials (2M) with $n = 10^4$ permutations.

6.5. Implementation details

The modules encoder, decoder, predictor and the disentanglers were modeled as multi-layer perceptrons comprising 2 hidden layers each. The encoder and decoder had 512 units in each layer, while the disentangler modules had 128 units in each layer. For the predictor modules, 256 and 512 units were used in the first and second hidden layers, respectively. The discriminator module comprised of a 1 hidden layer network with 64 hidden units. The probability of dropout used in the random perturbation module was set to 0.75.

Each model was trained using an early stopping criterion based on the speaker prediction accuracy on the embed-val dataset. In each epoch of the UAI-AT and UAI-MTL training, optimization was performed with 10 updates of secondary branch for every 1 update of the primary branch. A minibatch size of 128 was used, and the primary and secondary objectives were optimized using the Adam optimizer with $1e-3$ and $1e-4$ learning rates, respectively, and a decay factor of $1e-4$ for both. The dimensions for the embeddings $e_1$ and $e_2$ were chosen to be 128 and 32, respectively. We set the weights for the losses as $a = 100$, $b = 5$ and $\gamma = 100$. The architecture and loss weight parameters were chosen based on our previous work using the UAI technique to improve robustness of speaker embeddings (Peri et al., 2020b). For the discriminator module that is used in the proposed UAI-AT and UAI-MTL methods, we tuned the weight on the bias term denoted by $\delta$ in Eq. (4), by evaluating several models with different weight values on the eval-dev dataset. Table A.7 in Appendix A shows the fairness (auFaDR-FAR) and utility (%EER) of systems that were trained with different bias weights on the eval-dev dataset. For each method, the model that gave the best performance (in terms of the auFaDR-FAR on the eval-dev dataset) was used for final evaluations reported in the next section on the held-out eval-test dataset.

7. Results and discussion

In this section, we report results from the experiments described in Section 6, and discuss our findings. First, we compare the fairness of the proposed systems against the baselines at a range of system operating points in Section 7.1. We then discuss how these systems compare in terms of their utility in Section 7.2. Finally, in Section 7.3, we delve into biases present in the ASV systems at the score level (before the thresholding operation shown in Fig. 1). This sheds light on the biases present in the verification similarity score distribution of the existing ASV systems, and how the proposed techniques mitigate these biases.

7.1. Fairness

Fig. 3 shows FaDR plotted at various demographic-agnostic FAR values (up to 10%) for the proposed UAI-AT and UAI-MTL methods in comparison with the baseline x-vector systems, on the eval-test dataset. We focus on operating points below 10% FAR because systems operating at FAR values beyond that may not be useful in practice.

The demographic-agnostic FAR values are obtained by applying different thresholds on all verification pairs pooled irrespective of the demographic attribute of the utterances. FaDR is plotted for 3 values of the error discrepancy weight ($\omega$ in Eq. (5)), denoting varying amount of contribution from the differences between the genders in FRR and FAR. $\omega = 0.0$ corresponds to differences in FRR alone (Fig. 3(a)), while $\omega = 1.0$ corresponds to differences in FAR alone (Fig. 3(b)). $\omega = 0.5$ corresponds to equal contribution of differences in FARs and FRRs (Fig. 3(c)).

Discussion: From Fig. 3(a), we observe that the x-vector systems (red and orange curves) score high on the fairness metric when $\omega = 0.0$. This implies that FRR, which is the rate of incorrectly rejecting genuine verification pairs, has minimal dependence on the gender of the speaker. As we discuss later in Section 7.3, this can be explained from the similarity scores of the x-vector speaker embeddings for the genuine pairs shown in Fig. 6(b), where we observe a substantial overlap in scores of the female and male populations. Furthermore, we observe that the proposed ASV systems (UAI-AT and UAI-MTL) score similar to the baselines. It can be inferred that if we only care about the FRRs (i.e., how many genuine verification pairs are rejected by the ASV system), then the x-vector systems are already fair with respect to the gender attribute, and additional processing using the proposed methods retains the existing fairness.

On the other hand, as shown in Fig. 3(b), the x-vector systems (red and orange curves) are less fair considering the case of $\omega = 1.0$. This shows that for the baseline systems, FAR, which is the rate of incorrectly accepting impostor verification pairs, depends on the gender of the speakers. Particularly, the x-vector system trained with imbalanced data scores lower on the fairness metric compared
Fig. 3. Fairness (binary gender groups) at different operating points characterized by demographic-agnostic FAR up to 10%, evaluated using 3 different values for the error discrepancy weight (Eq. (5)), $\omega = 0.0$, 1.0 and 0.5. Higher values of FaDR indicate better fairness. Different values of $\omega$ allow evaluating fairness as measured by different error types. When evaluating fairness using discrepancy in FRR alone ($\omega = 0.0$), there is not much difference between the different systems. All systems seem to perform well with FaDR close to 100%. When evaluating fairness using discrepancy in FAR alone ($\omega = 1.0$), baseline x-vector-B trained on balanced data performs better than x-vector-U. However, the proposed systems (UAI-AT and UAI-MTL) outperform x-vector-B. When evaluating fairness using weighted discrepancy in FAR and FRR with equal weights, the proposed systems still show better performance than the baselines. The decision of using techniques to improve fairness of baseline systems is application-specific. Applications requiring a higher emphasis on reduced disparity between demographic groups in accepting impostor verification claims (higher values of $\omega$) should benefit from the proposed techniques.

(a) FaDR with $\omega = 0.0$. Corresponds to discrepancy in FRR between demographic groups. Useful in applications with emphasis on reducing gender disparity in rejecting genuine verification pairs. Equals $100 - (|\%\text{FRR}^f_1 - \%\text{FRR}^m_2|)$

(b) FaDR with $\omega = 1.0$. Corresponds to discrepancy in FAR between demographic groups. Useful in applications with emphasis on reducing gender disparity in accepting impostor verification pairs. Equals $100 - (|\%\text{FAR}^f_1 - \%\text{FAR}^m_2|)$

(c) FaDR with $\omega = 0.5$. Corresponds to equal contribution of discrepancies in FAR and FRR between genders to the fairness metric. Useful in applications with emphasis on reducing gender disparity both in rejecting genuine verification pairs and accepting impostor verification pairs. Equals $100 - (0.5\times|\%\text{FRR}^f_1 - \%\text{FRR}^m_2| + 0.5\times|\%\text{FAR}^f_1 - \%\text{FAR}^m_2|)$

Furthermore, the fairness of both the x-vector systems drops at higher values of demographic-agnostic FAR. This suggests that data balancing by itself may not achieve the desired fairness at all operating regions of the ASV system considering the biases in FARs between genders. Previous works in domains other than ASV made similar observations. For example, Wang et al. (2019) showed that data balancing may not be sufficient to address biases, and they attribute such behavior to bias amplification by models. Recently, in the field of ASR, Garnerin et al. (2021) showed that when training with balanced datasets, the actual speaker composition in the training data plays a key role in the biases observed in the system outputs. We observe that using the proposed techniques to transform the x-vector speaker embeddings by including demographic information during training (UAI-AT and UAI-MTL) improves the fairness of systems considering the biases in FARs between the female and male population. The FaDR values ($\omega = 1.0$) of the proposed methods (green and blue curves) remain close to 100% at different values of the demographic-agnostic FAR. Therefore, in scenarios where we care about how many impostor verification pairs are incorrectly accepted by the ASV systems, the proposed embedding transformation techniques are beneficial in improving fairness with respect to gender.
FaDR) at all values of demographic-agnostic FAR between 1% and 10% in Fig. 3. \( \omega \) in FRR). UAI-MTL improves fairness while retaining utility (similar %EER as x-vector-B), while UAI-AT achieves desired fairness at the cost of reduced utility.

Baseline and proposed systems are trained on unbalanced data (orange curve), the system trained with data balanced with respect to the genders (red curve) performs better in terms of fairness across all operating points. This confirms the observation by Fenu et al. (2020b), that data balancing helps improve the fairness of speaker verification systems to some extent. The proposed UAI-MTL and UAI-AT methods (green and blue curves) consistently perform better than the baselines in terms of fairness at all operating points (with the exception of UAI-AT at FAR=1%, where it is only slightly lower than the x-vector-B system). These results suggest that both adversarial and multi-task learning of speaker embeddings using gender labels can further improve the fairness of speaker representations compared to data balancing techniques.

An additional observation from the plots in Fig. 3 is that the benefits in terms of fairness compared to the baselines are more prominent at higher FARs. This is evident from the increasing difference between the FaDR values of the baseline x-vector-B and the proposed systems as the demographic-agnostic FAR increases. As we will see later in Section 7.3, this behavior can be explained by the distribution of the verification scores. Also, FaDR only captures the absolute discrepancy in the performance between genders, but does not provide information about which particular demographic group is impacted. We discuss the performance of the systems separately for each gender group in Appendix B.

### 7.2. Fairness-utility analysis

Table 5 shows the area under the FaDR-FAR curve (auFaDR-FAR) along with the %EER capturing utility on eval-test dataset. The UAI-MTL method achieves significantly higher auFaDR-FAR values than the baseline x-vector-B for all values of \( \omega \). In contrast the UAI-AT method has a reduced fairness compared to the baseline. This suggests that the UAI-MTL technique to improve fairness generalizes across datasets, while the performance improvements from the UAI-AT technique seems to be inconclusive across datasets. Similar observations can be made with the AT technique, where performance gains observed in other datasets are not transferred to voxceleb-H. The values in bold denote the highest fairness for each different value of \( \omega \). Omitting the results from x-vector-U, NLDR and UAI based on observations in Table 5.

### Table 5

AuFaDR-FAR capturing fairness (binary gender groups) for 5 different values of \( \omega \), and %EER capturing utility on eval-test dataset. Both the UAI-AT and UAI-MTL methods achieve similar AuFaDR-FAR values, higher than the baseline x-vector-B for all values of \( \omega \), with significant improvement from x-vector-B for \( \omega = 1.0 \) (when discrepancy only in FAR between genders is considered) and \( \omega = 0.75, 0.5 \) (when discrepancy in FAR is weighted higher or equal to the discrepancy in FRR). UAI-MTL improves fairness while retaining utility (similar %EER as x-vector-B), while UAI-AT achieves desired fairness at the cost of reduced utility.

The upper bound for auFaDR-FAR is 900, corresponding to perfect fairness (= 100% FaDR) at all values of demographic-agnostic FAR between 1% and 10% in Fig. 3.
the x-vector-B baseline at $\omega = 1.00, 0.75, 0.50$. This validates the statistical significance of the findings reported in the previous section. Additionally, we observe that the UAI-MTL method provides markedly better utility (as shown by the lower %EER) than the UAI-AT system. This is also evident from Fig. 4, where we observe that the UAI-MTL method (green curve) performs similar to the baseline x-vector-B speaker embeddings (red curve) in terms of speaker verification performance. Though the UAI-AT method performs similar to the UAI-MTL method in terms of fairness (auFaDR-FAR in Table 5), it comes at the cost of degraded utility relative to the baseline x-vector-B speaker embeddings (shown by the shift of the blue curve away from the origin in Fig. 4). In summary, we find that the proposed multi-task method of transforming speaker embeddings can improve fairness to supplement data balancing techniques, while having minimal impact on utility (with statistically insignificant increase from 2.47 to 2.70). In contrast, the adversarial training method UAI-AT improves fairness at the cost of a significant increase in the %EER (from 2.47 to 3.86). This suggests that multi-task learning using the UAI-MTL framework to transform speaker embeddings provides greater benefits than adversarial methods considering both improvement in the fairness of ASV systems and their impact on utility.

We observe from the ablation studies that the NLDR and UAI techniques to transform speaker embeddings are not effective at improving fairness. This shows that merely using speaker labels without the demographic information cannot provide improvements in fairness over pre-trained speaker embeddings. This implies that the discriminator in Fig. 2 is an indispensable module to mitigate biases present in existing speaker representations, as noted in previous work (Jaiswal et al., 2019). We also observe that MTL (without the UAI branch) is not effective in improving fairness. Even though AT shows some promise, we observe that the utility takes a hit (higher %EER). Furthermore, we show in Appendix A that adversarially trained methods (UAI-AT and AT) have greater variation in %EER with respect to the contribution of the bias term on the training loss ($\delta$ in Eq. (4)). This makes it challenging to tune the bias weight. Also, as we discuss later using results on the voxceleb-H dataset, the AT and MTL techniques (without the UAI branch) do not generalize well to out-of-domain datasets. These experiments suggest that both the discriminator and the disentangler modules play an important role in developing fair speaker representations using the proposed methods. Aligned with the observations made in Section 7.1, we note the relationship between the benefits of the proposed systems and the error discrepancy weight $\omega$ in Table 5. The proposed methods are more beneficial in applications emphasizing discrepancy in FAs (higher values of $\omega$) than those with emphasis on FRs (smaller values of $\omega$).

Results on the out-of-domain voxceleb-H test set are shown in Table 6. We observe that the UAI-MTL technique to transform x-vector-B speaker embeddings attains the best performance in terms of fairness (highest auFaDR-FAR), and utility (lowest %EER). This suggests generalizability of multi-task training using the UAI framework when evaluated on a different dataset that is unseen during training. We also observe that, performance improvements over the baselines using UAI-AT and AT techniques are inconsistent comparing with the results on the eval-test data shown in Table 5, while UAI-MTL shows conclusive performance improvements even on out-of-domain (real-world interview) data. We also performed experiments on the standard Voxceleb-O dataset, and observed that the %EER improves from 24.07% (x-vector-B) to 22.31% (UAI-MTL), while the fairness measured by auFaDR-FAR at $\omega = 0.5$ improves from 826.8 to 838.6. This further validates the generalizability of the proposed methods.

7.3. Biases in verification scores

Measures of fairness and utility are obtained after applying a threshold on the speaker verification scores as shown in Fig. 1. We have quantitatively observed that the fairness of ASV systems can be improved through the UAI-AT and UAI-MTL techniques

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10 The seemingly poor performance of utility of all the methods on the voxceleb-H dataset can be attributed to the utility of the x-vector speaker embeddings that we begin with. Here, our goal was to improve fairness of speaker embeddings, while retaining their utility.

11 https://wwwrobots.ox.ac.uk/~vgg/data/voxceleb/meta/veri_test2.txt
Fig. 5. Kernel density estimates of cosine similarity scores of impostor pairs (where test utterance belongs to speaker different from claimed identity) for the female and male demographic groups. Can be used to explain FAs. Both the x-vector baselines have the scores of the female population shifted compared to the scores of the male population, though training on balanced data (x-vector-B) seems to reduce the differences compared to x-vector-U. Transforming the x-vectors using UAI-AT and UAI-MTL techniques reduces differences between the scores of the female and male populations. Particularly, UAI-MTL produces scores with barely noticeable difference between the genders shown by the %intersection in the scores between genders. This helps explain the observed improvement in fairness in Table 5 when considering the discrepancy in FAR between the female and male demographic groups ($\omega = 1.0$).

Discussion: First, we notice from Fig. 5(a) that there exists a skew in the cosine similarity scores between the female and male populations in the x-vector system trained on data imbalanced with respect to the genders. This points to the presence of biases, likely exacerbated by the training data imbalance. Particularly, we notice that the impostor scores for the female demographic population are higher than the scores of the male population, suggesting that at a given threshold, the proportion of FAs for the female population would be higher than for the male population. Such differences between the female and male impostor scores have been documented in prior literature (Marras et al., 2019). Further, from Fig. 5(b) it can be observed that training using data balanced with respect to the gender labels can mitigate the skew to some extent. Finally, we observe from Figs. 5(c), 5(d) that both the adversarial and multi-task learning techniques can further reduce the skew between the female and male verification scores. In particular, the UAI-MTL method produces almost overlapping score distributions for the female and male populations. This suggests that transformation of the speaker embeddings using gender information in a multi-task fashion using the UAI-MTL framework can help mitigate the biases in the impostor verification scores between genders. Subsequent application of a threshold on these scores would therefore produce similar rates of FAs for the female and male populations, as we have seen in Section 7.1.

From Figs. 6(a) and 6(b), we notice that the scores of the genuine pairs between the female and male demographic groups are mostly overlapping. This implies that at any given threshold, we would not observe much difference between the proportions of FRs of the demographic groups. This is consistent with the quantitative analysis shown earlier in Table 5, where we found high values of the auFaDR-FAR metric for the x-vector systems computed at smaller values of $\omega$ (corresponding to greater emphasis on differences compared to the baseline x-vector systems. However, the primary source for lack of fair performance in ASV systems is the biases present in the speaker verification scores (Stoll, 2011). In order to understand the biases present in the ASV systems, we perform a qualitative analysis of the verification scores similar to the work by Toussaint and Ding (2021). In particular, we plot the kernel density estimate plots of the cosine similarity scores of the impostor verification pairs for the female and male populations in Fig. 5, and those of the genuine pairs in Fig. 6. The impostor verification scores determine the FARs, while the scores of the genuine verification pairs determine the FRRs of the systems.
Kernel density estimates of cosine similarity scores of genuine pairs (where test utterance belongs to same speaker as the claimed identity) for the female and male demographic groups. Can be used to explain FRs. Both the x-vector baselines have the scores of the female and male population overlapping with each other, indicating minimal bias between genders. This helps explain the high level of fairness observed in Table 5 when considering the discrepancy in FRR between the female and male demographic groups ($\omega = 0.0$). It is worth noting that both the transformation techniques (UAI-AT and UAI-MTL) retain this overlap as shown by the %intersection in the scores between genders.

We observe from Figs. 6(c) and 6(d) that embedding transformation using the proposed methods retains the unbiased nature of the genuine verification scores obtained from the pre-trained embeddings. In summary, we show that the proposed methods improve or retain the fairness depending on the target use-case. In scenarios where the rates of false accepts are an important consideration, the proposed UAI-AT and UAI-MTL methods are able to reduce the biases present in existing speaker representations. When the false rejects are more important, our methods preserve the fairness of existing speaker representations.

8. Conclusions and future directions

We presented adversarial and multi-task learning strategies to improve the fairness of extant speaker embeddings with respect to demographic attributes of the speakers. In the adversarial setting, the demographic attribute labels were used to learn speaker embeddings devoid of the demographic information. In the multi-task approach, the goal was to learn demographic-aware speaker embeddings, where the demographic information is explicitly infused into the embeddings. In particular, we adopted the unsupervised adversarial invariance (UAI) framework (Jaiswal et al., 2019) to investigate whether adversarial or multi-task training is better suited for reducing the biases with respect to binary gender groups in speaker embeddings used in ASV systems. We used the recently proposed fairness discrepancy rate metric (de Freitas Pereira and Marcel, 2021) to evaluate the fairness of the systems at various operating points. We observed that data balancing, a commonly used strategy to improve fairness, mitigates the biases to some extent. However, its fairness depends on the operating point of interest (whether it is a low FAR or low FRR operating region). Therefore it is important to consider the specific application — and the corresponding desired operating region — of the ASV systems when evaluating fairness. For applications strictly focused on the differences between genders in their FRRs, existing x-vector speaker embeddings (either trained on balanced or imbalanced data) performed well by having very minimal biases, and the speaker embeddings transformed using the proposed methods retained this desirable property. However, as we move toward applications focused on the differences between the genders in their FARs, the x-vector speaker embeddings showed biases between the genders. In this scenario, the proposed adversarial and multi-task training strategies were able to mitigate these biases by a
Table A.7

Classification results on embed-val dataset and verification results on eval-dev dataset for different bias weights ($\delta$ in Eq. (4)). The %EER for xvector-U and xvector-B was 2.66 and 2.36 respectively, while the auFaDR was 871.09 and 884.57 respectively. The majority class random chance accuracy for bias labels in the embed-val data was 70%.

| Bias weight | Method    | %acc. (predictor) | %acc. (bias) | %EER | auFaDR | Method    | %acc. (predictor) | %acc. (bias) | %EER | auFaDR |
|-------------|-----------|-------------------|--------------|------|--------|-----------|-------------------|--------------|------|--------|
| 10          | UAI-AT    | 96.99             | 78.24        | 2.81 | 893.40 | AT        | 96.72             | 69.91        | 3.00 | 879.68 |
| 30          | UAI-AT    | 96.91             | 70.55        | 3.42 | 892.17 | AT        | 96.71             | 76.04        | 3.40 | 882.82 |
| 50          | UAI-AT    | 96.58             | 75.92        | 4.95 | 893.03 | AT        | 96.65             | 71.91        | 3.14 | 897.04 |
| 70          | UAI-AT    | 96.76             | 80.35        | 3.12 | 896.38 | AT        | 96.24             | 59.37        | 9.78 | 884.28 |
| 100         | UAI-AT    | 96.6              | 82.03        | 4.11 | 890.21 | AT        | 95.91             | 78.10        | 8.11 | 884.06 |
| 150         | UAI-AT    | 96.1              | 77.70        | 4.58 | 888.12 | –         | –                 | –            | –    | –      |
| 200         | UAI-AT    | 95.3              | 72.80        | 10.26| 893.69 | –         | –                 | –            | –    | –      |
| 10          | UAI-MTL   | 97.04             | 97.03        | 2.45 | 896.72 | MTL       | 96.68             | 97.19        | 2.47 | 861.27 |
| 30          | UAI-MTL   | 96.99             | 97.98        | 2.66 | 885.45 | MTL       | 96.70             | 98.33        | 2.52 | 876.25 |
| 50          | UAI-MTL   | 96.96             | 98.52        | 2.7  | 886.52 | MTL       | 96.79             | 98.71        | 2.77 | 858.71 |
| 70          | UAI-MTL   | 97.01             | 98.73        | 3.06 | 858.99 | MTL       | 96.75             | 98.91        | 2.99 | 852.92 |
| 100         | UAI-MTL   | 96.96             | 98.86        | 2.66 | 848.88 | MTL       | 93.73             | 98.96        | 2.75 | 870.16 |
| 150         | UAI-MTL   | 96.94             | 99.02        | 2.98 | 851.31 | –         | –                 | –            | –    | –      |
| 200         | UAI-MTL   | 96.91             | 99.03        | 3.19 | 852.62 | –         | –                 | –            | –    | –      |

We trained several models by varying the weight parameter $\delta$ in Eq. (4). This parameter allowed us to control the influence of the discriminator loss on the overall optimization. As described in Section 6, we fixed the values for the weights of the predictor, decoder and disentangler modules based on preliminary experiments to $\alpha = 100$, $\beta = 5$ and $\gamma = 100$ respectively. Therefore, by varying $\delta$ we studied the isolated effect of the discriminator loss on the training objective.

Discussion: The third set of columns in Table A.7 shows the speaker classification accuracy of the predictor and gender classification accuracy of the discriminator on the embed-val dataset. Clearly, the UAI-AT method is able to reduce the gender significant margin. Furthermore, we showed qualitative evidence that the proposed methods were able to effectively reduce the biases in the verification score distributions between the female and male populations. In addition, we showed that it is critical to jointly consider aspects of both fairness and utility in selecting embedding transformation techniques. We found that the adversarial and multi-task training strategies showed similar performance on fairness metrics. However, while multi-task training to transform the x-vector speaker embeddings had very little impact on the utility, the adversarial training strategy significantly degraded the utility.

We explored several aspects of fairness and utility of ASV systems in this work. However, we believe that there are still open questions that require further investigation. We have limited our analyses to gender as the demographic factor of interest in our investigations. However, considering other demographic attributes (including intersectional demographics) is important (Foulds et al., 2020). For example, systems that are not biased with respect to the gender alone could be biased when a different demographic factor (e.g. age) is considered as an intersecting attribute. Also, we trained our models using the MCV corpus, and analyzed the biases in these systems using the MCV and Voxceleb corpora. However, such datasets could be prone to systemic censoring (Kallus and Zhou, 2018). For example, the MCV corpus may not be sufficiently representative of the different demographic groups and their intersectional attributes, because the data was collected only from users with access to a microphone and internet connection. Similarly the Voxceleb corpus consists of speech samples only from celebrities. A more inclusive adoption of such technologies requires careful consideration of these various aspects, which we hope to address in future research. Finally, we adopted notions of biases which belong to the category of group fairness (ensuring errors of the system are similar for different groups). However, individual fairness, which is an alternate way of evaluating biases, can also provide interesting insights into how these systems behave.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Effect of bias weight

We trained several models by varying the weight parameter $\delta$ in Eq. (4). This parameter allowed us to control the influence of the discriminator loss on the overall optimization. As described in Section 6, we fixed the values for the weights of the predictor, decoder and disentangler modules based on preliminary experiments to $\alpha = 100$, $\beta = 5$ and $\gamma = 100$ respectively. Therefore, by varying $\delta$ we studied the isolated effect of the discriminator loss on the training objective.
classification accuracy to close to majority class chance performance (70%). This shows that the technique is able to successfully reduce the amount of gender information in the speaker embeddings. On the other hand, owing to its multi-task training setup, the UAI-MTL method retains gender information in the speaker embeddings (>97% gender classification accuracy).

Verification results on the eval-dev dataset are shown in the fourth set of columns in Table A.7. We notice that compared to the UAI-AT models, the UAI-MTL models provide better verification performance as shown by the %EER in all settings. In addition, across different training configurations (characterized by the bias weights), the UAI-MTL method has a smaller variation in %EER (min: 2.45, max: 3.19) when compared with the UAI-AT method (min: 2.81, max: 10.26). This provides further evidence of the negative impact on the utility of adversarial training when compared with multi-task learning. It validates the findings from prior research that have shown the instability of adversarial training (Sadeghi et al., 2021). We find similar trends in models trained without the UAI branch. Specifically, we observe that the MTL methods have a smaller variation in %EER (min: 2.47, max: 2.99) when compared to the AT methods (min: 3.00, max: 9.78). Finally, for all the methods, we choose the optimal bias weight $\delta$ based on the best auFaDR-FAR value (in bold). This model was used for the evaluations on the eval-test dataset that were described in Section 7.

Appendix B. Direction of bias

The results using FaDR metric shown in Section 7 considers the absolute difference between the FARs and FRRs of the female and male demographic groups. It does not provide a sense of the direction of bias. Previous studies have shown that ASV systems are prone to higher error rates for the female population than the male population (George et al., 2015; Fenu et al., 2020a). In a similar vein, we wanted to investigate if there is a systematic bias against a particular gender. In particular, we wanted to check if the ASV systems consistently underperform for a particular demographic group when compared with a different demographic group. We report the individual FARs (B.7) and FRRs (Fig. B.8) of the female and male populations at varying thresholds characterized by demographic-agnostic %FAR.

Discussion: From Fig. B.7, we observe that the baseline x-vector system is highly biased against the female demographic groups considering FARs. This is evident from the gap between the curves for the male (solid blue) and female (dotted blue) populations. Furthermore, the gap increases at higher values of demographic-agnostic %FAR. On the other hand, both the proposed UAI-AT and UAI-MTL methods reduce the gap in %FAR between the female and male populations. However, they show noticeably different behavior. The UAI-MTL reduces the %FAR of the female population (dotted red) compared to the x-vector baseline, while simultaneously increasing the %FAR of the male population (solid red), bringing them closer to each other. On the other hand, the
UAI-AT method substantially reduces the %FAR on the female population (dotted green), while also reducing the %FAR on the male population (solid green) by a small extent. At first glance, this seems to suggest that UAI-AT is a better technique since it improves the performance of both demographic groups with respect to %FAR. However, as we discussed in Section 7.2, considering the %FRR of the systems, UAI-AT method degrades the performance, thereby affecting the overall utility of the ASV system.

In Fig. B.8, we report the %FRR for the female and male populations. Notice the difference in the scale of y-axis compared to Fig. B.7. Here, we observe that there is not much difference between the %FRRs of the different demographic groups even with the baseline x-vector system. Furthermore, we observe that the UAI-MTL method to transform x-vectors does not have a substantial impact on the performance compared with x-vectors. The UAI-AT technique of transforming x-vectors increases %FRR for both the female and male populations to some extent.

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