Mitigating Subgroup Disparities in Speech Models: A Divergence-Aware Dual Strategy

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***Abstract*—Speech models may exhibit disparities in performance across different population subgroups. Prior mitigation efforts often rely on the manual user-driven selection of predefined data subgroups of interest. However, they fail to correctly identify all relevant subgroups associated with performance issues.**

We propose to mitigate performance disparities of subgroups that underperform, i.e., exhibit a *divergence*, relative to overall model performance. We tackle the performance disparities from two alternative perspectives - an in-processing one, implementing mitigation measures during model development, and a post-processing one, refining already trained models. For the in-processing scenario, we propose two approaches: a divergence-based regularization and a data augmentation technique to boost subgroup performance during model fine-tuning. The post-processing strategy introduces a divergence-aware data acquisition method to prioritize acquiring samples from underperforming subgroups. Experiments on a dataset for Automatic Speech Recognition, one for Emotion Recognition, and two datasets for Intent Classification in English and Italian highlight the improvement achieved by the divergence-aware strategies, which significantly reduce performance disparities and outperform traditional clustering-, KNN-, error-driven-, and random-based methods.

***Index Terms*—bias mitigation, spoken language understanding, speech processing, data acquisition, divergence**

I. Introduction

THE advances in speech and language technologies have transformed how we interact with machines over the past few years. These innovations have become ubiquitous in our daily lives, from voice-activated virtual assistants to language translation tools. However, as these models become more pervasive, there is also a growing concern about potential disparities in their behavior. Biases present in training data, linguistic variations, and disparate data representation can inadvertently lead to unequal outcomes, affecting certain subgroup populations more than others. Recent studies revealed model bias and disparate treatment in data subgroups ([1]–[7]), emphasizing the need for addressing these issues. Identifying and mitigating these disparities is crucial to ensure that speech and language technologies are fair and robust across subpopulations.

Current mitigation solutions often rely on a priori knowledge or user-driven selection of the subgroups of interest. These strategies primarily focus on the diversity and robustness of the data, addressing challenges related to linguistic variations, recording conditions, environment, and demographics [8]. However, these approaches may overlook unexpected subgroups associated with performance issues. Moreover, disparities may emerge at the intersection of multiple challenging characteristics. Recent advancements in mitigation solutions identify data subgroups (i.e., clusters) automatically [1]. However, the identified subgroups lack interpretability, as they are based on clustering speaker embeddings. Hence, they do not provide interpretable descriptions of the underlying data instances, thus not allowing the identification of the source of disparities. Consequently, these approaches cannot guide targeted data acquisition to mitigate disparities.

In this paper, we propose to mitigate the performance disparities within data subgroups that deviate significantly, i.e., exhibit a *divergence*, from the overall model performance. We propose two alternative mitigation strategies, in-processing and post-processing. In-processing involves the implementation of mitigation measures during the model development phase [9]. Post-processing refers to mitigating an already trained model [9]. We perform mitigation of a pre-trained model after it has undergone fine-tuning for a specific downstream task. For the identification of the underperforming subgroups, we leverage the techniques of [10], [11] that define subgroups as interpretable combinations of metadata such as speaker demographics, recording conditions, and task characteristics.

In the in-processing scenario, we perform mitigation during model development. We propose two methods: divergence-aware regularization and divergence-aware data acquisition. As for regularization, we introduce a novel regularization term directly associated with the divergence of each subgroup. This term emphasizes subgroups showing a more pronounced performance disparity. During model training, samples belonging to subgroups with higher divergence, i.e., greater differences from overall model performance, receive greater attention. For data augmentation, we augment audio samples belonging to subgroups where the model underperforms by applying diverse transformations. This subgroup-based data augmentation increases the representation of more difficult samples, thus improving model robustness and performance at the subgroup level.

As a post-processing strategy, we propose divergence-aware data acquisition. Given an already trained model, we guide the data acquisition process by focusing on subgroups with lower-than-average performance. Being the subgroups interpretable, we can, for example, reveal that our model exhibits lower performance on utterances of women speaking fast, and we acquire samples with such metadata.

The alternative yet complementary in-processing and post-processing strategies offer versatility to accommodate diverse application needs, usability constraints, and purposes. Practitioners can opt for one strategy or the other based on their specific requirements, whether it be improving a trained

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model, the feasibility of collecting additional samples, or the goal of directly training a subgroup-regularized model.

We evaluated our approaches on the LIBRISPEECH [12] dataset for Automatic Speech Recognition (ASR), IEMOCAP [13] for Emotion Recognition (ER), and two Spoken Language Understanding (SLU) datasets for intent classification, FSC [14] for the English language and ITALIC [15] for Italian. We employ the transformer-based wav2vec 2.0 [16] model for the IC and ER English datasets, the multilingual XLS-R [17] model for ITALIC, and Whisper [18] for LIBRISPEECH. The experimental findings underscore the effectiveness of our approaches in mitigating performance disparities. Specifically, our post-processing method demonstrates that targeted sample acquisition improves subgroups and overall model performance compared to existing clustering-based, KNN, and error-driven baselines and indiscriminate data acquisition. In the case of our in-processing techniques, we show their ability to reduce disparities during the training process, with the regularization slightly outperforming the subgroup-based data augmentation, enabling the direct development of models with enhanced fairness and equity in the outcomes. We also evaluate the joint adoption of our mitigation strategies. Combining the in- and post-processing techniques leads to further improvements by addressing disparities from complementary perspectives.

We introduced a preliminary version of this work in [19], which only focused on the divergence-aware data acquisition process applied to intent classification tasks. This paper proposes a complete approach to subgroup disparity mitigation by introducing two novel in-processing techniques. In-process mitigation allows the reduction of disparities even when data acquisition campaigns may not be feasible. This expanded framework provides a more flexible solution to address subgroup disparities across various practical scenarios, enhancing its applicability.

Our main contributions are the following.

- **In-processing mitigation techniques.** We introduce two novel in-processing techniques that mitigate disparities in data subgroups at training time. We boost the performance of divergent subgroups (i) through regularization and (ii) via data augmentation during the training process.
- **Post-processing mitigation techniques.** We outline and extensively evaluate the post-processing technique firstly introduced in [19], that mitigates disparities in data subgroups for a trained model via a divergence-aware data acquisition.
- **Design tips for mitigation.** We provide a discussion on the nuances of in- and post-processing subgroup disparities mitigation techniques, guiding practitioners in the choice of the most suitable technique for the scenario at hand.
- **Combination of mitigation strategies.** We evaluate the impact of jointly applying multiple mitigation strategies, assessing and discussing the benefit of their integration.

The source code and its documentation to adopt our approach and reproduce the results are available at `https://github.com/koudounasalkis/DADS`.

We organized the paper as follows. Section II reviews the related works. Section III describes our dual strategy. Section IV presents the experimental setting. Section V reports the main experimental results. Finally, Section VI draws the conclusions.

II. RELATED WORK

The increasing use of speech systems has raised concerns about potential biases, leading to various recent studies exploring different aspects of bias and disparity [2], [4], [10], [20]–[27]. These works generally address the challenges related to linguistic variations, recording conditions, environment, and demographics [8]. Several works have examined racial bias [2], [20], performance disparities across gender, dialects, and race [23] or age [4], and the impact of gender representation in speech corpora [24], [25]. Other works investigated disparities at the intersection of speech and demographic information [10], [21], [22]. Studies have also questioned conventional evaluation metrics [26] and introduced corpora [27] to identify demographic bias in speech applications.

Some techniques propose to address disparities during the training process, such as via domain adversarial training [28], or counterfactual modifications of dependent variables, such as the speaker's voice [29]. Privacy-preserving techniques that extract utterance level embeddings using a speaker ID model and group embedding adaptation have also been explored for fairness improvement in ASR and Speaker Verification systems [30], [31]. The considered groups are user-defined and known a priori. In contrast, our approach mitigates disparities of automatically identified subgroups where the model behaves differently. As a result, we boost overall and subgroup-level performance.

Recent work on acquisition-based techniques addressed the question of how many data samples we should acquire from each group to improve model performance using learning curves [32], [33], given a set of groups of interest. The work in [28] also explores data augmentation for known critical subgroups, such as non-native speakers, to augment training data. Closer to our work, the approach in [1] automatically groups data by clustering speaker embeddings and identifies the clusters that exhibit inferior performance for a given ASR model. Data acquisition considers data samples close to the problematic clusters. However, these clusters, unlike our subgroups, are not interpretable. Subgroup interpretability allows for guiding the data acquisition process, collecting data with specific properties. Non-interpretable subgroups instead only allow selecting from already-available data, e.g., by feeding it into an encoder model that extracts embeddings.

The work in [34] identifies subgroups defined by attribute combinations but concentrates on under-represented subgroups. We instead focus on all subgroups with adequate representation in data on which the model *under-performs*, be it for a trained model or during the training process, so that we can acquire more data or boost the model to address this issue specifically. Combining these approaches could offer a two-fold solution for bias mitigation.

III. A Dual Strategy for Mitigation

Our approach to mitigating bias and improving fairness in a model, either already trained or during training[1], involves two main steps: (i) automatic identification of subgroups (Section III-A) and (ii) divergence-aware mitigation. In the first step, we extract interpretable subgroups and compute how the model performs on these subgroups compared to its overall performance. The second step involves either post-processing through targeted data acquisition (Section III-B) or in-processing mitigation III-C), depending on whether we consider an already trained model or actively training one.

A. Automatic Subgroup Identification

Consider a dataset of utterances D. We annotate each utterance with a set of interpretable metadata. These can be speaker-related features, such as gender or age, or speaking and recording features, such as utterance duration, presence of noise, and speaking rate. The metadata can be either already pre-existing and available in the dataset, such as the self-reported gender and age of the speaker, or automatically derived [10] from utterances, such as the speaking rates, utterance duration, and words per second. Therefore, no additional manual annotation is necessary for this metadata. A data subgroup S is a subset of the dataset D sharing the same set of metadata. We represent a subgroup as a conjunction of attribute-value pairs. For example, the subgroup $\{$*gender=female, duration>5s*$\}$ represents utterances of female speakers with a duration greater than 5s.

Consider a model M and a subgroup S. $f(S, \mathcal{M})$ denotes a performance measure (e.g., accuracy) of M on subgroup S. The *divergence* [11] of subgroup S for model M and measure f, denoted $\Delta_f(S, \mathcal{M})$, quantifies the difference between the model performance on subgroup S and its performance on the entire dataset D:

$$\Delta_f(S, \mathcal{M}) = f(S, \mathcal{M}) - f(D, \mathcal{M}) \ . \tag{1}$$

The higher the divergence, the more its performance diverges from the overall one. For example, a high negative divergence in accuracy for a subgroup indicates the model performs poorly on utterances of that subgroup compared to overall.

We adopt the identification procedure described in [10] to derive metadata, extract subgroups, and compute their divergence. Specifically, we use the DivExplorer [11], [35], [36] approach, which identifies all subgroups with an adequate representation in the dataset based on a frequency threshold, denoted minimum support $minsup$. The support threshold $minsup$ (such as 0.1% of the dataset) controls the exploration and ensures that the subgroups contain enough utterances to make the performance computation statistically significant. This is critical as performance measures on subgroups with small support can be subject to statistical fluctuations. The resulting subgroups, denoted as *frequent*, can overlap. For example, the subgroup $\{$*gender=female, duration>5s*$\}$ overlaps with $\{$*gender=female*$\}$.

[1]In our work, we fine-tune the pre-trained self-supervised models. In the rest of the paper, we will use both training and fine-tuning without distinction to refer to the fine-tuning process.

In summary, given a dataset with annotated metadata, a model M, and a performance measure of interest f, we identify the set of frequent subgroups $\mathcal{S}$. For each $S \in \mathcal{S}$, we have its divergence $\Delta_f(S, M)$, and the statistical significance t of the divergence computed with the Welch t-test. This information about divergent subgroups where the model underperforms enables us to actively address these issues, either post-processing through targeted data acquisition (Section III-B),in-processing via regularization or data augmentation (Section III-C), or both.

B. Post-processing mitigation

Post-processing mitigation involves mitigating subgroup disparities of an already trained model. We propose addressing these disparities by acquiring data from subgroups where the model underperforms and subsequently training it on the (old and) newly collected set of data. In the following, we describe this methodology.

Divergence-aware Data Acquisition*:* Let $\mathcal{S}$ be the set of frequent subgroups, and each subgroup $S \in \mathcal{S}$ is characterized by divergence $\Delta_f(S, \mathcal{M})$ for the performance measure f. We define $\mathcal{S}^- \subseteq \mathcal{S}$ as the set of *challenging* subgroups for which model $\mathcal{M}$ has lower performance than the average. For performance measures for which the higher, the better (e.g., accuracy, F1 measure), $\mathcal{S}^-$ consists of the subgroups that have negative divergence, i.e., $\mathcal{S}^- = \{S \in \mathcal{S} | \Delta_f(S) < 0\}$. We can easily modify this definition to apply to the opposite case (e.g., word error rate, the lower, the better).

We perform a pruning step to reduce redundancy among the challenging subgroups, following the pruning approach outlined in [11]. During this pruning process, when presented with two subgroups, S_a and S_b, where S_b includes S_a along with an additional metadata condition, we retain only the more general S_a if the absolute difference in the divergence between the two subgroups falls below a predefined threshold. The rationale behind this approach is that S_a already represents the divergence of S_b, as the additional metadata of S_b only marginally affects the divergence. For instance, consider the subgroup $\{$*young_woman*$\}$ with a divergence of -0.39 and $\{$*young_woman, utterance_duration>10s*$\}$ with a divergence of -0.41. In this scenario, we preserve solely the former subgroup, as it accounts for most of the divergence observed in the latter. We denote the summarized set with $\dot{\mathcal{S}}^-$. Pruning the challenging subgroups results in a more concise representation and facilitates data acquisition, as we can focus on the most relevant subgroups.

Our subgroups are *interpretable*. Hence, we can specifically target the acquisition of data samples with characteristics of the identified challenging subgroups. We target for performance improvement the top-K summarized challenging subgroups $\dot{\mathcal{S}}^-$ with the highest absolute divergence by acquiring data belonging to these subgroups and denote them with $\dot{\mathcal{S}}_k^-$. This selection of only the most divergent challenging subgroups allows us to control the targeted acquisition process.

Once we identify $\dot{\mathcal{S}}_k^-$, the mitigation process via data acquisition is straightforward. Specifically, we retrain the model by adding new data belonging to one or more of the K subgroups

(as subgroups can partially overlap, the same data instance can belong to more than one top-K subgroup).

More formally, let $\mathcal{T}$ be the training set and $\mathcal{U}$ a set of utterances unseen at training time. Utterance $x_i \in \mathcal{U}$ satisfies a subgroup S, denoted as $x_i \vdash S$, if its metadata values match S. The data acquisition consists of acquiring a set of new utterances $\mathcal{U}(\dot{\mathcal{S}}_k^-)$ satisfying at least a challenging group $\dot{\mathcal{S}}_k^-$, with $\mathcal{U}(\dot{\mathcal{S}}_k^-) = \{x_i \in \mathcal{U} \mid \exists S \in \dot{\mathcal{S}}_k^- : x_i \vdash S\}$. Finally, the mitigation step consists of retraining the entire model $\mathcal{M}$ of the enriched dataset $\mathcal{T} \cup \mathcal{U}(\dot{\mathcal{S}}_k^-)$. The parameter K allows us to control the data acquisition process. Our experiments will illustrate how the choice of K affects overall model performance as well as subgroup-specific performance.

C. In-processing mitigation

In-processing mitigation involves addressing disparities in data subgroups during model training. We propose to use the information of the subgroups where the model exhibits lower performance than average and their divergence for improving the model by operating either (i) on the model loss or (ii) on the data themselves.

For the former approach, we introduce a regularization term into the model loss. This term encourages the model to focus more on data samples from subgroups where performance diverges from the model's overall behavior. The regularization strength is proportional to the extent of this divergence. The latter approach involves data augmentation for samples within underperforming subgroups. By enriching the dataset with augmented versions of these samples, we aim to improve the model's ability to handle such challenging subgroups.

Divergence-Aware Regularization: We propose a divergence-based regularization term to mitigate subgroup disparities at training time. At each epoch, we derive subgroup divergence scores to guide the training process accordingly. Intuitively, the higher the divergence of a subgroup, the more the model deviates in modeling it compared to the overall data. Consequently, the model should focus on the data samples belonging to this subgroup to mitigate its divergent behavior. Essentially, the regularization term encourages the model to adjust its focus based on the degree of divergence, prioritizing data samples that belong to challenging subgroups. To implement this, the regularization applies a sample weighting mechanism based on the divergence. Samples from subgroups with higher divergence will have greater weights in the loss computation.

Let $\mathcal{T}$ and $\mathcal{V}$ be the training and validation sets. Given a model $\mathcal{M}_e$ at epoch e trained on $\mathcal{T}$, we extract the set $\mathcal{S}$ of frequent subgroups coupled with their divergence scores from the validation set $\mathcal{V}$. Let x_i be an utterance in $\mathcal{T}$, and y_i and $\hat{y}_i$ its true and predicted labels. We denote by $\mathcal{S}(x_i)$ the set of subgroups satified by x_i, with $\mathcal{S}(x_i) = \{S \in \mathcal{S} \mid x_i \vdash S\}$.

For each utterance x_i, we define a boosting weight as the highest absolute divergence across the subgroups to which x_i belongs:

$$w(x_i) = \max_{S \in \mathcal{S}(x_i)} |\Delta_f(S, \mathcal{M})| \tag{2}$$

We introduce the *divergence-based* loss L_Δ:

$$\mathcal{L}_\Delta = \sum_{x_i \in \mathcal{T}} w(x_i) \mathcal{L}_{CE}(y_i, \hat{y}_i) \tag{3}$$

where L_{CE} denotes the standard cross-entropy loss. Utterances associated with higher divergence will have a greater impact on the divergence-based loss $\mathcal{L}_\Delta$, as their weight will be higher. The final loss is defined as

$$\mathcal{L} = \alpha \mathcal{L}_{CE} + (1 - \alpha) \mathcal{L}_\Delta \tag{4}$$

where $\mathcal{L}_\Delta$ is the regularization term and α is weighting factor. The $\mathcal{L}_\Delta$ term allows the model to give more attention to utterances that exhibit larger divergences.

Algorithm 1 summarizes each step of our training strategy. We first initialize the boosting weights (Line 1) and extract metadata from the utterances in the training and validation sets (Line 2). Then, the training procedure iterates the following steps for all epochs. (i) Train the model with the training loss defined in Equation 4, (ii) Extract the subgroups with a frequency greater than s and their divergence scores using DIVEXPLORER (Line 5), (iii) For each utterance x_i in training set $\mathcal{T}$, derive the set of subgroups satisfying it, i.e., $\mathcal{S}(x_i)$ (Line 6), (iv) update the boosting weights w for each training instance via Equation 2 (Line 7). Finally, the algorithm returns the final boosted model (Line 9).

Algorithm 1 Divergence-Aware Regularization

Require: Training Set $\mathcal{T}$, Validation Set $\mathcal{V}$, min frequency s
Ensure: M: Model
1: Initialize weights $w(x_i) = 1.0 \ \forall x_i \in \mathcal{T}$
2: $\mathcal{T}_m, \mathcal{V}_m \leftarrow$ Derive metadata $\mathcal{T}, \mathcal{V}$
3: **for each** epoch $e \in E$ **do**
4: $\quad \mathcal{M}_e \leftarrow$ Model trained on $\mathcal{T}$ at epoch e via Eq. 4
5: $\quad \mathcal{S}, \Delta_f(S, \mathcal{M}_e) \forall S \in \mathcal{S} \leftarrow$ DIVEXPLORER($\mathcal{M}_e, \mathcal{V}_m$)
6: $\quad \mathcal{S}(x_i) \leftarrow$ Satisfy($x_i, \mathcal{S}$) $\quad \forall x_i \in \mathcal{T}_m$
7: $\quad w(x_i) \leftarrow$ ComputeWeights($x_i, \mathcal{S}(x_i)$) $\quad \forall x_i \in \mathcal{T}_m$ via Eq. 2
8: **end for**
9: **return** $\mathcal{M}_e$

Divergence-Aware Data Augmentation: While the regularization strategy adjusts the training process at the subgroup level by modifying the loss function, the data augmentation strategy operates on the data itself. In summary, at each epoch, we derive the subgroups where the model mostly underperforms. We perform data augmentation on the training samples belonging to at least one of those challenging subgroups and keep training the model on such an augmented dataset. Intuitively, the model can better learn such critical cases and improve performance by augmenting challenging samples.

More formally, being $\mathcal{V}$ the validation set and $\mathcal{M}_e$ the model at epoch e, we compute the top-K summarized challenging subgroups $\dot{\mathcal{S}}^-$ with the highest absolute divergence on $\mathcal{V}$ and for model $\mathcal{M}_e$. $\dot{\mathcal{S}}^-$, derived likewise to the post-processing technique, are the summarized subgroups on which the model most underperforms. Being $\mathcal{T}_b$ the batch of training data, we consider the set of utterances $\mathcal{T}_b(\dot{\mathcal{S}}_k^-)$ satisfying at least a

challenging group $\dot{\mathcal{S}}_k^-$, with $\mathcal{T}_b(\dot{\mathcal{S}}_k^-) = \{x_i \in \mathcal{U} \mid \exists S \in \dot{\mathcal{S}}_k^- : x_i \vdash S\}$. Again, this resembles the post-processing strategy, but in this case, the set is from the training rather than an unseen set. We then perform data augmentation on samples $\mathcal{T}_b(\dot{\mathcal{S}}_k^-)$. Data augmentation techniques include time stretching, background noise injection, reverberation, pitch shifting, or a random combination of these perturbations. Hence, the mitigation step consists of training the entire model $\mathcal{M}$ of such an augmented set. By augmenting these challenging samples, we provide the model with additional training instances that can help it better model the challenging subgroups.

IV. Experimental setting

A. Datasets

We evaluated our approach on three tasks: Intent Classification (IC), Emotion Recognition (ER), and Automatic Speech Recognition (ASR), focusing on datasets in both English and Italian languages. Specifically, we considered the following four datasets.

Fluent Speech Commands (FSC) [37] is a dataset in English for the IC task, including 30,043 utterances from 97 speakers. Each audio sample has three slots: action, object, and location, determining 31 distinct intents. We used the intent accuracy as target performance f.

ITALIC [15] is a dataset for IC in Italian containing 16,521 samples from 70 speakers. The action and scenario slots denote the intents for a total of 60 distinct intents. We considered the intent accuracy.

LibriSpeech [12] is a collection of audio recordings from audiobooks. We use the *"clean-360"* version, which includes 360 hours of clean audio samples. We evaluated the Word Error Rate (WER) performance metric for the ASR task.

IEMOCAP [13] - Interactive Emotional Dyadic Motion Capture is a dataset for the ER task. The dataset includes discrete emotion labels (i.e., happiness, anger, sadness, frustration, and neutral state) and continuous arousal annotations (i.e., activation, valence, and dominance). Following standard procedure [38], we considered four classes (neutral, happy, sad, angry) to have balanced emotion categories, resulting in a dataset of 4,990 samples. We used the emotion label accuracy as a target performance measure.

For FSC, ITALIC, and LibriSpeech datasets, we considered the official splits of train, validation, and test sets, with each speaker exclusively assigned to one set. The IEMOCAP dataset is divided into five sessions (i.e., splits) typically evaluated using a 5-fold cross-validation approach. In this study, we used three sessions as the training set, one as validation, and one as test set to match the configuration of the other datasets. As a result, we have the training, validation, and test sets for all four datasets. We evaluated the proposed mitigation techniques in two configurations. In the first configuration, we use the full train set for training the speech model. We then identify the frequent subgroups, their divergence, and the subset of challenging subgroups on the validation set. Finally, we evaluated the model performance on the test set. We adopted this configuration exclusively for the in-processing techniques as the post-processing data acquisition requires unseen labeled data. In the second configuration, we partitioned the training set, allocating 80% for training and holding out 20%. We ensured that each speaker was assigned to only one set, thus no speaker appeared in both the training and held-out sets. We used the held-out set to acquire data samples for the post-processing technique. We used the validation and test sets in the same way as the first configuration, maintaining consistency across all techniques. We use this configuration for all techniques, both post- and in-processing.

B. Metadata

We implemented the metadata enrichment as proposed in [21], considering demographic information, speaking and recording conditions, and dataset-specific metadata. Regarding speaker demographics, we considered all available (self-declared) demographic data, such as age, gender, and country of origin. We then extracted speech-oriented metadata, i.e., metadata related to the speech characteristics of the utterances. Specifically, we derived the number and the duration of silence (both total and trimmed), the word count, and the speaking rate (words per second). As dataset-dependent metadata, we analyzed metadata specific to each dataset and/or task. We used the intent slots for the FSC and ITALIC datasets and the emotion and arousal annotations for IEMOCAP. Continuous metadata was discretized into "low", "medium", and "high" bins using frequency-based discretization.

C. Models

We fine-tuned the pre-trained wav2vec 2.0 [16] base model for the FSC and IEMOCAP datasets, the multilingual XLS-R [17] model for ITALIC, and Whisper [18] base monolingual for LibriSpeech. We used the pre-trained checkpoints available on the Hugging Face hub [39].

D. Hypeparameter setting

In our subgroup extraction with DivExplorer, we explored all subgroups with a minimum frequency of 0.03, following [19]. The α weighting parameter for the regularization loss is set to 0.7 For both post-processing data acquisition and in-processing data augmentation, the hyperparameter K defines the top-K most challenging subgroups. We varied the value of K from 2 to 5, and we analyzed its impact on the results. For the core of the experiments, we use K=2 for both the data acquisition and targeted data augmentation as it has been shown to lead to the best results overall [19]. Specifically, K=2 corresponds to 226 additional samples for FSC, 154 for ITALIC, 112 for IEMOCAP, 6715 for LibriSpeech. We then studied the impact of varying K for a sensitivity analysis. Our fine-tuning process included a hyperparameter search and followed established procedures outlined in the relevant literature. Each IC and ER model undergoes fine-tuning by adding a final classification linear layer to the encoder architecture. Specifically, for IC and ER, we utilized a learning rate of 1e-4, a batch size of 32, a warmup ratio of 0.1, and a weight decay of 0.01. In the case of ASR,

we fine-tuned the entire Whisper base model, employing a learning rate of 1e-5, a batch size of 8, 500 warmup steps, and a weight decay of 0.01. For all models, we opted for the AdamW optimizer. The IC and ER models were trained for a maximum of 30 epochs with an early stopping criterion, while the ASR model underwent a maximum of 5 epochs of training. Experiments were run on a machine equipped with Intel® Core™ i9-10980XE CPU, $1 \times$ Nvidia® RTX A6000 GPU, 64 GB of RAM running Ubuntu 22.04 LTS.

E. Metrics

We evaluated the overall model performance using accuracy and macro F1 scores for FSC, ITALIC, and IEMOCAP and WER (Word Error Rate) and CER (Character Error Rate) for LIBRISPEECH. We also assessed the performance at the subgroup level. We focused on the most challenging subgroup, i.e., the subgroup that shows the most substantial decrease in performance compared to the overall average, denoted with Δ^{-}_{max}. Δ^{-}_{max} evaluates how well the model can reduce differences in performance and thus mitigate bias. We also computed the average divergence on the top 10, 20, and 50 subgroups with the highest decrease in performance (Δ^{-}_{avg-n}), along with the average absolute divergence across all identified subgroups ($\mid \Delta^{-}_{avg-all} \mid$). Note that, for LIBRISPEECH, a subgroup's poorer performance compared to the overall system is reflected by a larger divergence in its WER value. Therefore, unlike the divergence in accuracy for the other datasets, a positive WER divergence signifies reduced performance. These metrics enable us to quantify the effectiveness of the mitigation approach in addressing performance discrepancies across subgroups.

F. Baselines

We benchmark our in- and post-processing mitigation approaches against four alternative approaches to derive challenging samples to mitigate.

Random baseline. As a straightforward benchmark, we randomly select the challenging samples. This approach serves as a baseline for comparison and to demonstrate the need for subgroup-based and divergent-aware selection.

Cluster-based baseline [1]. We identify the challenging subgroups via unsupervised clustering, following the approach proposed in [1]. We tested two configurations of embeddings. In the former (`clustering`), we first extract acoustic embeddings from audio samples in the validation set, that is, the last hidden state representations of the adopted models (i.e., wav2vec 2.0 base for FSC and IEMOCAP, XLS-R for ITALIC, and Whisper for LIBRISPEECH). In the latter, we used speaker embeddings, specifically employing x-vector features [40], which have been demonstrated to be effective for ASR [1] (we refer to this baseline as $\texttt{clustering}_{\texttt{X}}$ in Tables). We apply K-means clustering to group them into similar clusters. Following [1], we used 50 clusters for LIBRISPEECH as they are proven to adequately capture speech characteristics pertinent to ASR. We instead considered 10 clusters for ITALIC and 20 for FSC, as these configurations have been found to achieve the best performance on the target datasets [19]. For IEMOCAP, we also examined 20 clusters as this configuration led to the best results overall. We then select the set of clusters with the poorest performance, representing the challenging subgroups in the model that exhibit the lowest performance. We finally take challenging samples based on their proximity to these identified subgroups.

KNN baseline. We employ a K-Nearest Neighbors (KNN) technique. We assess whether an utterance is challenging for the model or not by conducting a majority vote among its neighbors in the validation set, considering instances where the model incorrectly classifies them. K is chosen by optimizing performance, i.e., identifying challenging subgroups, on the validation set. Specifically, we use K equal to 14 for FSC, 11 for ITALIC, 12 for IEMOCAP, and 18 for LIBRISPEECH.

Error-driven baseline [41]. We adopt an error-driven approach, similar to the technique introduced in [41]. Following the model's training phase, we identify instances within the held-out set that the model predicts inaccurately. These instances are labeled as challenging and are subsequently incorporated into the augmented training data. We apply this technique exclusively for post-processing mitigation, as addressing erroneous samples is inherently embedded within standard loss terms during model training. Note that this baseline assumes prior knowledge of the ground truth labels on the held-out set for the tasks at hand.

V. EXPERIMENTAL RESULTS

This section outlines the results and findings of our experiments, focusing on the effectiveness of our mitigation strategies compared to baseline approaches. We assess their performance improvements both overall and in data subgroups (Section V-A). We first evaluate the setup using the hold-out dataset derived from the original training set, allowing us to assess both in- and post-processing methods. We then examine the results when utilizing the entire training set, thus focusing only on the in-processing approach. Finally, we conduct a sensitivity analysis to investigate how varying the number of challenging subgroups impacts post-processing data acquisition and in-processing divergence-aware data augmentation (Section V-B).

A. Mitigation results

1) Comparison against baselines: Tables I and II show the mitigation results of our in- and post-processing strategies compared with the baselines for FSC and ITALIC and for IEMOCAP and LIBRISPEECH, respectively. We use a consistent configuration, using a part of the original train set for actual training and a part of held-out for the data acquisition. This setting ensures the comparability of the results, as we use the same train, validation, and test sets. For each dataset, we report the model's overall and subgroup-based performance results without any mitigation, denoted as *'original.'* We then report the results for the post-processing and the two in-processing strategies. For each strategy, we evaluate our approach compared to the baselines, varying how we identify the challenging data samples for the mitigation process. Finally, we outline the results when we train on the

TABLE I

MEAN AND STANDARD DEVIATION RESULTS OF THREE RUNS ON THE CONSIDERED IC DATASETS. ORIGINAL FINE-TUNING AND MITIGATION STRATEGIES, INCLUDING ACQUISITION, REGULARIZATION, AND TARGETED DATA AUGMENTATION (TARGET DATA++), CONSIDERING THE ORIGINAL TRAINING SET DIVIDED INTO TRAINING AND HELD-OUT SETS, K=2. BEST RESULTS FOR EACH DATASET ARE IN **BOLD**, SECOND-BEST UNDERLINED; BEST RESULTS FOR EACH DATASET AND STRATEGY IN LIGHT YELLOW.

DS	*Method*	*Strategy*	*Accuracy*	*F1 Macro*	Δ^-_{max}	Δ^-_{avg-10}	Δ^-_{avg-20}	Δ^-_{avg-50}	$\lvert\Delta_{avg-all}\rvert$
FSC	original	-	91.58±0.08	86.34±0.13	-70.09±0.26	-70.09±0.26	-65.73±0.49	-53.31±0.19	1.06±0.07
	w/ random	acquisition	92.56±0.44	90.25±0.60	-52.20±2.57	-51.11±2.19	-46.61±1.34	-43.98±0.68	0.97±0.02
	w/ KNN	acquisition	92.07±0.17	89.92±0.11	-49.90±0.33	-49.85±0.29	-49.76±0.27	-46.98±0.28	0.96±0.03
	w/ clustering	acquisition	89.77±0.88	87.02±0.15	-47.37±0.42	-47.34±0.42	-47.23±0.43	-46.75±0.91	0.94±0.04
	w/ clustering$_X$	acquisition	91.44±0.65	90.12±0.66	-47.99±0.53	-47.95±0.52	-47.80±0.49	-47.11±0.44	0.89±0.05
	w/ error-driven	acquisition	95.71±0.74	94.06±0.83	-48.13±0.39	-48.02±0.36	-47.58±0.35	-45.97±0.48	0.92±0.04
	ours	acquisition	**96.55±0.08**	94.71±0.12	-40.60±0.35	-40.28±0.36	-38.08±0.36	-32.72±0.28	0.81±0.03
	w/ random	target data++	92.85±0.75	92.29±0.68	-45.67±2.78	-45.59±2.75	-43.41±2.68	-41.28±2.51	0.84±0.27
	w/ KNN	target data++	93.94±0.28	93.15±0.31	-43.61±1.32	-43.34±1.24	-42.12±1.19	-38.84±1.08	0.75±0.03
	w/ clustering	target data++	94.49±0.41	94.31±0.44	-40.09±2.12	-39.95±2.03	-39.77±1.84	-34.65±1.07	0.38±0.10
	w/ clustering$_X$	target data++	95.12±0.44	95.02±0.45	-41.13±1.89	-41.01±1.85	-40.45±1.74	-39.89±1.61	0.37±0.06
	ours	target data++	95.75±0.37	95.48±0.35	-36.12±0.39	-35.98±0.37	-34.77±0.36	-32.65±0.33	0.35±0.04
	w/ random	regularization	93.41±0.52	93.22±0.67	-44.51±6.59	-44.25±6.55	-44.04±6.21	-38.54±5.85	0.85±0.14
	w/ KNN	regularization	95.11±0.21	95.04±0.20	-41.32±3.52	-41.19±3.28	-40.51±3.15	-36.95±2.75	0.62±0.05
	w/ clustering	regularization	95.75±0.39	95.49±0.41	-39.51±5.68	-39.18±5.21	-37.29±4.74	-34.74±4.18	0.43±0.02
	w/ clustering$_X$	regularization	96.04±0.38	95.99±0.36	-39.88±4.17	-39.80±4.14	-38.71±4.03	-36.13±3.98	0.38±0.03
	ours	regularization	96.47±0.11	**96.33±0.12**	**-34.49±0.45**	**-34.49±0.45**	**-34.11±0.41**	**-31.34±0.32**	**0.29±0.01**
	original	all data	93.42±0.17	93.11±0.17	-53.18±0.15	-50.89±0.09	-45.61±0.14	-40.37±0.16	0.37±0.01
ITALIC	original	-	73.79±0.32	68.08±0.37	-47.63±1.93	-47.52±1.94	-47.15±1.92	-43.31±1.78	0.60±0.01
	w/ random	acquisition	75.32±0.63	70.72±0.58	-47.00±0.81	-46.86±0.80	-46.22±0.77	-42.68±0.70	0.48±0.02
	w/ KNN	acquisition	75.56±0.57	70.21±0.54	-46.11±0.93	-46.02±0.92	-45.49±0.84	-42.17±0.74	0.39±0.02
	w/ clustering	acquisition	74.05±0.33	69.09±0.75	-45.02±2.02	-44.91±2.01	-44.14±1.81	-39.79±1.33	0.37±0.08
	w/ clustering$_X$	acquisition	76.19±0.37	71.04±0.64	-46.51±1.87	-46.48±1.85	-45.77±1.63	-42.48±1.29	0.37±0.01
	w/ error-driven	acquisition	77.14±0.52	72.65±0.63	-46.97±1.15	-46.84±1.07	-45.91±1.02	-42.36±0.93	0.45±0.04
	ours	acquisition	**77.40±0.24**	72.51±0.14	-31.75±0.55	-31.71±0.55	-31.11±0.41	-28.19±0.18	0.34±0.03
	w/ random	target data++	75.14±0.49	73.01±0.79	-46.89±2.05	-46.51±1.98	-44.98±1.57	-42.04±1.36	0.35±0.12
	w/ KNN	target data++	75.97±0.34	73.67±0.39	-41.19±1.17	-40.53±1.06	-38.57±0.95	-35.77±0.89	0.31±0.03
	w/ clustering	target data++	76.59±0.84	73.98±0.78	-38.95±2.69	-38.37±2.43	-37.01±2.20	-34.15±2.02	0.28±0.04
	w/ clustering$_X$	target data++	76.94±0.65	74.01±0.67	-39.62±2.29	-39.57±2.25	-38.43±2.11	-35.04±1.87	0.25±0.03
	ours	target data++	77.12±0.54	74.05±0.42	-31.93±1.91	-31.58±1.85	-30.05±1.59	-28.19±1.35	0.23±0.05
	w/ random	regularization	76.04±0.71	72.11±0.55	-46.58±2.29	-46.22±2.21	-45.87±2.08	-43.16±1.97	0.33±0.11
	w/ KNN	regularization	76.54±0.44	73.08±0.39	-41.23±1.24	-41.04±1.17	-38.63±1.02	-35.78±0.87	0.29±0.04
	w/ clustering	regularization	76.67±0.79	74.01±0.76	-38.43±2.51	-38.05±2.18	-36.59±1.96	-33.93±1.79	0.25±0.03
	w/ clustering$_X$	regularization	76.98±0.58	74.16±0.53	-39.15±2.21	-39.11±2.17	-37.89±2.05	-34.14±1.85	0.24±0.03
	ours	regularization	77.02±0.61	**74.19±0.48**	**-31.54±2.02**	**-31.14±1.93**	**-29.88±1.74**	**-28.10±1.67**	0.21±0.05
	original	all data	75.71±0.36	73.22±0.33	-47.54±0.79	-47.36±0.76	-46.68±0.47	-41.93±0.00	**0.15±0.03**

complete training set, i.e., when we acquire the entire held-out set, we denote this experiment as *'all data.'* In the following, we outline the main outcomes and findings.

Our dual strategy outperforms the baselines. Our in- and post-processing approaches consistently outperform all the baselines, as highlighted in light yellow in the tables. Our approaches not only achieve higher overall performance in accuracy and F1 for IC and ER tasks, and WER and CER for the ASR task, but they also significantly improve subgroup-based performance. Specifically, our methods lead to the highest reduction in the divergence of the most underperforming subgroup (Δ^-_{max}), in the average divergence of top 10, 20, and 50 underperforming subgroups (Δ^-_{avg-n}) and of the average absolute divergence across all groups ($\mid \Delta^-_{avg-all} \mid$).

For the post-processing data acquisition, our technique is followed by the error-driven baseline for the overall performance. This finding aligns with the intuitive notion that acquiring instances where the model fails can enhance performance. However, clustering emerges as the runner-up method for improving subgroup-based performance. This observation underscores the intuitive strategy of prioritizing the data acquisition efforts towards subgroups (clusters in this case) where the model underperforms the most.

For the in-processing techniques, the clustering strategy is again the runner-up approach, exhibiting superior results both overall and at the subgroup level compared to the other baselines. This outcome holds for both targeted data augmentation and regularization. Interestingly, the baseline leveraging speaker embeddings (`clustering`$_X$) outperforms the other cluster-based variant in terms of overall accuracy and F1 Macro scores, yet shows lower performance on subgroup-level metrics, with the exception of $\mid \Delta^-_{avg-all} \mid$. Note that we exclude supervised baselines here, as error optimization is intrinsic in the training process and loss function.

TABLE II
MEAN AND STANDARD DEVIATION RESULTS OF THREE RUNS ON IEMOCAP AND LIBRISPEECH DATASETS. ORIGINAL FINE-TUNING AND MITIGATION STRATEGIES, INCLUDING ACQUISITION, REGULARIZATION, AND TARGETED DATA AUGMENTATION (TARGET DATA++), CONSIDERING THE ORIGINAL TRAINING SET DIVIDED INTO TRAINING AND HELD-OUT SETS; K=2. BEST RESULTS FOR EACH DATASET ARE IN **BOLD**, SECOND-BEST UNDERLINED; BEST RESULTS FOR EACH DATASET AND STRATEGY IN LIGHT YELLOW.

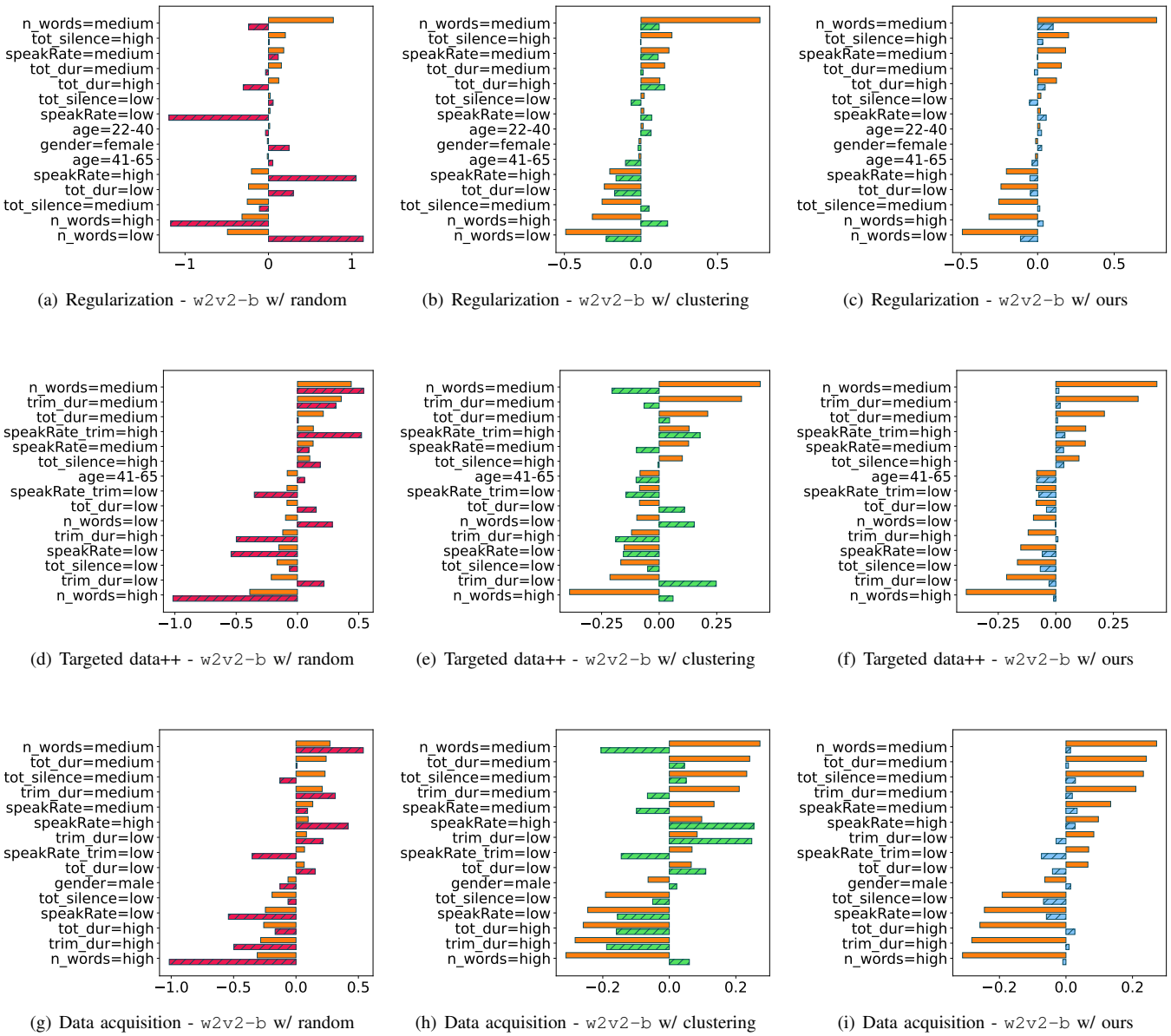
DS	*Method*	*Strategy*	*Accuracy*	*F1 Macro*	Δ^-_{max}	Δ^-_{avg-10}	Δ^-_{avg-20}	Δ^-_{avg-50}	$\lvert\Delta_{avg-all}\rvert$
IEMOCAP	original	-	63.80±0.24	52.44±0.22	-44.79±0.79	-44.41±0.75	-43.68±0.63	-43.01±0.59	2.15±0.04
	w/ random	acquisition	65.91±0.32	53.15±0.35	-42.38±0.93	-42.17±0.89	-41.61±0.77	-39.56±0.74	2.01±0.16
	w/ KNN	acquisition	66.17±0.19	53.59±0.14	-39.85±0.43	-39.80±0.42	-39.02±0.38	-37.19±0.29	1.84±0.03
	w/ clustering	acquisition	65.79±0.48	53.03±0.46	-39.04±0.73	-38.77±0.70	-38.13±0.66	-34.19±0.57	1.39±0.06
	w/ clustering$_X$	acquisition	67.12±0.51	55.18±0.53	-40.23±0.69	-40.19±0.65	-39.28±0.61	-35.96±0.53	1.21±0.05
	w/ error-driven	acquisition	68.19±0.26	55.44±0.27	-40.82±0.39	-40.70±0.37	-40.24±0.24	-38.97±0.19	1.75±0.04
	ours	acquisition	68.45±0.22	55.89±0.21	-33.71±0.29	-33.59±0.28	-33.01±0.21	-29.86±0.15	0.93±0.02
	w/ random	target data++	66.04±1.03	53.67±0.97	-41.13±1.15	-41.04±1.07	-40.55±0.89	-38.98±0.84	1.84±0.55
	w/ KNN	target data++	66.15±0.18	53.64±0.16	-39.72±0.45	-39.51±0.39	-38.79±0.35	-36.35±0.26	1.76±0.04
	w/ clustering	target data++	67.44±0.37	56.17±0.38	-36.19±0.58	-36.03±0.53	-35.28±0.41	-32.03±0.37	0.83±0.05
	w/ clustering$_X$	target data++	68.51±0.23	56.34±0.20	-37.71±0.48	-37.66±0.45	-36.84±0.39	-33.18±0.34	0.67±0.06
	ours	target data++	**68.93±0.19**	56.41±0.16	-33.04±0.17	-32.71±0.17	-31.88±0.14	-28.93±0.11	0.59±0.03
	w/ random	regularization	67.51±0.98	55.13±0.95	-40.02±1.01	-39.78±0.96	-39.11±0.82	-37.62±0.69	1.38±0.27
	w/ KNN	regularization	68.03±0.12	55.82±0.15	-38.09±0.34	-37.95±0.31	-37.03±0.25	-35.44±0.19	1.02±0.02
	w/ clustering	regularization	68.39±0.28	56.88±0.25	-35.41±0.47	-35.07±0.43	-34.15±0.39	-31.29±0.30	0.45±0.03
	w/ clustering$_X$	regularization	68.65±0.21	56.91±0.18	-36.13±0.51	-36.10±0.49	-35.88±0.42	-32.18±0.34	0.37±0.05
	ours	regularization	68.89±0.15	**56.95±0.13**	**-32.19±0.12**	**-31.04±0.10**	**-29.57±0.09**	**-27.11±0.07**	**0.21±0.02**
	original	all data	67.15±0.13	56.13±0.17	-41.10±0.24	-40.56±0.21	-40.08±0.20	-37.11±0.14	0.88±0.02

DS	*Method*	*Strategy*	*WER*	*CER*	Δ^-_{max}	Δ^-_{avg-10}	Δ^-_{avg-20}	Δ^-_{avg-50}	$\lvert\Delta_{avg-all}\rvert$
LIBRISPEECH	original	-	8.05±0.05	2.80±0.04	26.11±0.98	26.02±0.95	25.57±0.89	23.11±0.76	0.29±0.06
	w/ random	acquisition	7.14±0.09	2.38±0.08	17.74±0.61	17.50±0.57	17.12±0.51	16.09±0.44	0.22±0.09
	w/ KNN	acquisition	7.03±0.04	2.32±0.06	14.95±0.47	14.73±0.41	14.19±0.35	13.81±0.32	0.13±0.04
	w/ clustering	acquisition	6.42±0.07	2.01±0.06	12.38±0.52	12.26±0.48	12.07±0.43	11.59±0.37	0.09±0.05
	w/ clustering$_X$	acquisition	6.35±0.09	2.00±0.04	13.43±0.64	13.40±0.61	12.78±0.56	12.09±0.49	0.08±0.03
	w/ error-driven	acquisition	6.32±0.03	2.01±0.04	17.09±0.58	16.87±0.53	16.22±0.45	14.79±0.36	0.21±0.07
	ours	acquisition	6.31±0.04	1.99±0.04	9.51±0.36	9.38±0.29	9.02±0.25	7.87±0.16	0.07±0.03
	w/ random	target data++	6.89±0.15	2.25±0.14	17.44±0.57	17.28±0.53	17.07±0.42	16.01±0.34	0.17±0.10
	w/ KNN	target data++	6.41±0.07	2.12±0.04	13.19±0.32	13.11±0.26	12.64±0.21	11.38±0.11	0.12±0.06
	w/ clustering	target data++	5.95±0.08	1.92±0.09	11.72±0.38	11.48±0.32	11.09±0.24	10.65±0.20	0.08±0.05
	w/ clustering$_X$	target data++	5.86±0.06	1.90±0.05	12.81±0.47	12.80±0.45	12.37±0.41	11.76±0.38	0.07±0.04
	ours	target data++	5.82±0.04	1.87±0.06	9.27±0.17	9.01±0.14	8.55±0.12	7.72±0.09	0.04±0.02
	w/ random	regularization	6.74±0.17	2.17±0.15	17.51±0.49	17.33±0.47	16.92±0.38	15.84±0.35	0.15±0.09
	w/ KNN	regularization	6.24±0.05	2.05±0.05	13.04±0.26	12.79±0.23	12.08±0.17	10.70±0.12	0.11±0.05
	w/ clustering	regularization	5.80±0.07	**1.83±0.06**	10.98±0.41	10.56±0.38	10.01±0.32	9.47±0.24	0.06±0.03
	w/ clustering$_X$	regularization	5.74±0.06	**1.83±0.05**	11.27±0.38	11.24±0.36	10.98±0.29	10.16±0.25	0.04±0.02
	ours	regularization	**5.71±0.07**	**1.83±0.05**	**9.12±0.11**	**8.81±0.09**	**8.14±0.08**	**7.59±0.05**	**0.03±0.02**
	original	all data	6.31±0.07	1.98±0.06	14.71±0.85	14.55±0.79	13.98±0.76	13.01±0.68	0.11±0.03

In-processing techniques outperform post-processing. Addressing subgroup performance directly during model training proves more effective in mitigating subgroup disparities than operating on an already trained model. As we observe from Tables I and II, the divergence-aware regularization and the targeted data augmentation consistently yield lower scores for Δ^-_{max}, Δ^-_{avg-n}, and $\mid \Delta^-_{avg-all} \mid$ compared to the data acquisition across all evaluated datasets.

Divergence-aware regularization yields the best results. In-processing regularization outperforms the in-processing data augmentation and the post-processing technique. The approach demonstrates superior performance both in overall metrics and at the subgroup level.

2) Analysis of subgroup mitigation process: We further analyze the impact of the mitigation process on subgroup divergence. We can be interested in studying which metadata are generally associated with lower performance (or higher) than the average in the original model and how the mitigation process impacts such divergent behavior. For this analysis, we use the notion of Global Shapley value (GSV), as described in [10]. The GSV estimates the contribution of each metadata (e.g., *'gender=Female'*) to the divergence across all extracted subgroups. The higher the value, the more the metadata value is associated with different performance than overall ones. For instance, consider the in-processing regularization strategy and the FSC dataset. Figure 1 (top) shows the top-15 metadata values Global Shapley values before (orange) and after mitigation (shaded) for using the random baseline, clustering baseline, and our proposed approach. The random baseline fails to reduce the Global Shapley values, with some values even



(a) Regularization - `w2v2-b` w/ random (b) Regularization - `w2v2-b` w/ clustering (c) Regularization - `w2v2-b` w/ ours

(d) Targeted data++ - `w2v2-b` w/ random (e) Targeted data++ - `w2v2-b` w/ clustering (f) Targeted data++ - `w2v2-b` w/ ours

(g) Data acquisition - `w2v2-b` w/ random (h) Data acquisition - `w2v2-b` w/ clustering (i) Data acquisition - `w2v2-b` w/ ours

Fig. 1. **Global Shapley values (GSV).** Comparison of the top-15 *GSV* of the original model (orange) with random- (shaded red, left), clustering - (shaded green, middle), and *ours* divergence-aware (shaded blue, right) weighting. **Top**: (i) in-processing regularization; **Middle**: (ii) targeted data augmentation; **Bottom**: (iii) post-processing strategy. wav2vec 2.0 base (`w2v2-b`), FSC dataset.

increasing. This confirms the inability of the random-based mitigation to address subgroup disparities. On the other hand, the clustering-based approach generally reduces the values, showing the benefit of addressing mitigation at the subgroup level. Notably, our approach achieves the most substantial reduction in these global contributions. Similar considerations also apply to the in-processing targeted augmentation strategy, as shown in Figure 1(middle), as well as the post-processing acquisition scenario depicted in Figure 1(bottom). Across all scenarios, our approach consistently demonstrates significantly better performance in minimizing global contributions, effectively flattening them towards zero.

3) In-processing mitigation with the complete training set: Table III shows the mitigation results of our in-processing strategies compared with the baselines using the *complete* training set for FSC and ITALIC. Note that we only consider in-processing techniques as post-processing data acquisition requires separate and unseen data. The results confirm that our approaches overcome the baselines in both overall and subgroup metrics and that regularization is more effective than targeted data augmentation. They also demonstrate that as the number of training samples increases, our in-processing methods enable us to achieve better performance compared to the results shown in Table I, as one might have expected intuitively.

B. Sensitivity analysis

We study how varying the number of challenging subgroups K impacts the data augmentation and data acquisition ap-

TABLE III

MEAN AND STANDARD DEVIATION RESULTS OF THREE RUNS ON THE CONSIDERED IC DATASETS. ORIGINAL FINE-TUNING AND IN-PROCESSING MITIGATION STRATEGIES, INCLUDING REGULARIZATION AND TARGETED DATA AUGMENTATION (TARGET DATA++) WITH K=2, CONSIDERING *all* AVAILABLE TRAINING DATA. BEST RESULTS FOR EACH DATASET ARE IN **BOLD**, SECOND-BEST UNDERLINED; BEST RESULTS FOR EACH DATASET AND STRATEGY IN LIGHT YELLOW.

DS	*Method*	*Strategy*	*Accuracy*	*F1 Macro*	Δ^{-}_{max}	Δ^{-}_{avg-10}	Δ^{-}_{avg-20}	Δ^{-}_{avg-50}	$\lvert\Delta_{avg-all}\rvert$
FSC	original	-	93.42±0.17	93.11±0.17	-53.18±0.15	-50.89±0.09	-45.61±0.14	-40.37±0.16	0.37±0.01
	w/ random	target data++	94.91±0.87	94.46±0.86	-42.62±2.94	-42.51±2.88	-41.80±2.72	-37.19±2.38	0.36±0.24
	w/ KNN	target data++	96.72±0.34	96.15±0.39	-40.01±1.59	-39.59±1.57	-38.61±1.32	-34.09±0.99	0.31±0.08
	w/ clustering	target data++	97.85±0.37	97.59±0.65	-37.57±2.68	-37.21±2.49	-36.13±2.32	-32.75±2.07	0.24±0.11
	w/ clustering$_X$	target data++	98.19±0.31	98.05±0.29	-38.18±2.51	-38.16±2.50	-37.45±2.44	-34.03±2.27	0.23±0.08
	ours	target data++	98.46±0.11	98.42±0.17	-27.51±0.56	-27.12±0.52	-26.84±0.48	-22.15±0.43	0.21±0.08
	w/ random	regularization	96.46±0.56	96.29±0.66	-41.31±7.00	-41.31±7.00	-41.14±7.04	-40.66±7.15	0.79±0.94
	w/ KNN	regularization	97.55±0.28	97.38±0.24	-38.29±2.34	-38.02±2.25	-36.56±2.01	-32.15±1.54	0.53±0.06
	w/ clustering	regularization	97.88±0.33	97.65±0.57	-36.95±8.44	-36.28±8.21	-33.69±7.24	-30.74±6.48	0.13±0.02
	w/ clustering$_X$	regularization	98.25±0.28	98.09±0.31	-37.86±7.15	-37.84±7.12	-36.19±7.02	-32.57±6.85	0.12±0.02
	ours	regularization	**98.47±0.11**	**98.43±0.14**	**-24.49±0.57**	**-24.49±0.57**	**-24.11±0.51**	**-22.09±0.38**	**0.11±0.01**
ITALIC	original	-	75.71±0.36	73.22±0.33	-47.54±0.79	-47.36±0.76	-46.68±0.47	-41.93±0.00	0.15±0.03
	w/ random	target data++	76.06±0.29	73.36±0.77	-45.82±1.89	-45.34±1.72	-44.65±1.39	-40.82±1.10	0.13±0.09
	w/ KNN	target data++	77.15±0.21	74.03±0.24	-37.87±0.89	-37.12±0.83	-36.41±0.74	-34.04±0.67	0.12±0.04
	w/ clustering	target data++	77.81±0.56	74.19±0.49	-36.73±2.53	-36.19±2.27	-34.15±2.02	-32.58±1.84	0.08±0.02
	w/ clustering$_X$	target data++	77.94±0.43	74.51±0.40	-37.88±2.41	-37.84±2.38	-36.79±2.25	-33.81±2.08	0.06±0.02
	ours	target data++	78.01±0.49	74.74±0.35	-30.49±1.77	-30.02±1.52	-27.48±1.47	-24.73±1.21	0.05±0.03
	w/ random	regularization	77.47±0.22	72.76±0.22	-45.11±1.41	-44.99±1.40	-44.24±1.33	-39.58±1.14	0.10±0.01
	w/ KNN	regularization	77.96±0.19	74.12±0.23	-36.39±1.17	-36.14±1.09	-33.87±0.98	-30.05±0.91	0.07±0.02
	w/ clustering	regularization	78.01±0.45	74.45±0.35	-32.81±2.35	-32.73±2.32	-32.13±2.38	-28.97±2.16	0.05±0.03
	w/ clustering$_X$	regularization	78.05±0.51	74.63±0.52	-34.04±2.12	-34.01±2.09	-33.67±1.98	-30.18±1.82	0.04±0.02
	ours	regularization	**78.07±0.53**	**74.85±0.30**	**-30.10±1.71**	**-29.64±1.70**	**-27.31±1.66**	**-24.09±2.19**	**0.01±0.04**

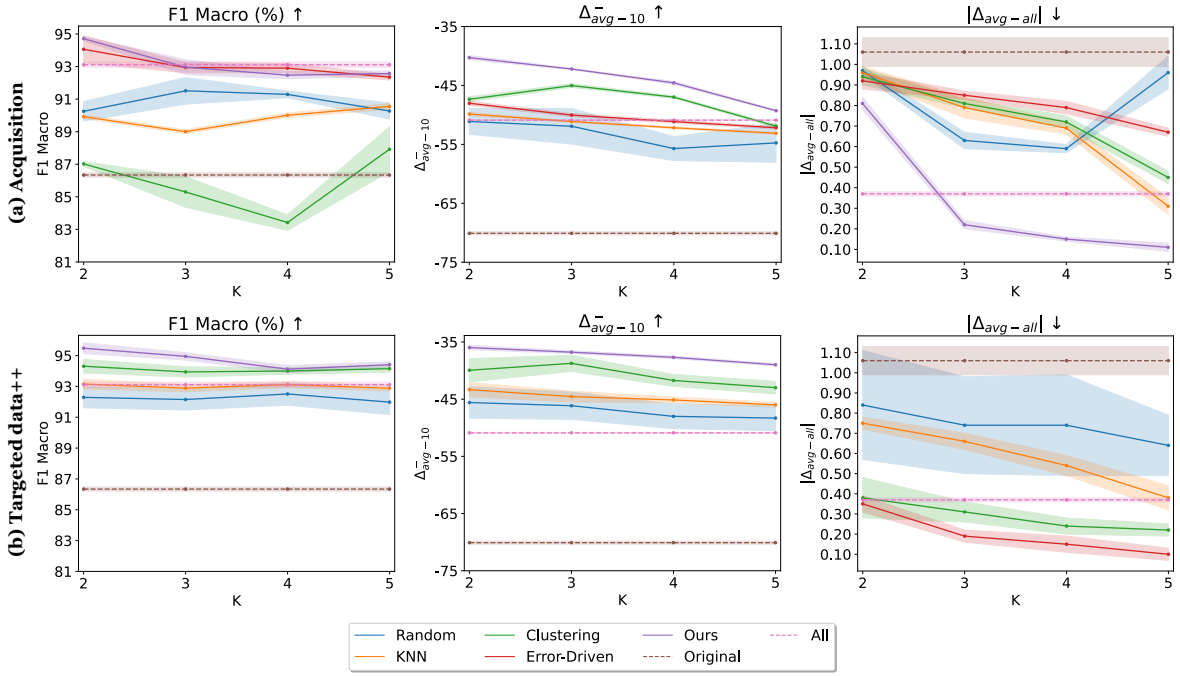


Fig. 2. **Sensitivity Analysis on K - FSC dataset**. F1 Macro (left), Δ^{-}_{avg-10} (middle), and $|\Delta_{avg-all}|$ (right) for the considered approaches in (a) the post-processing acquisition (up) and (b) in-processing targeted data augmentation (down) settings, varying K from 2 to 5; wav2vec 2.0 base model.

proaches. We do not examine the effect on the regularization as it does not depend on the number of challenging groups.

Figures 2 and 3 show the impact of K on mitigation results for the FSC and LIBRISPEECH datasets, respectively. The top part reports the results for the post-processing acquisition strategy, while the bottom one is the in-processing targeted data acquisition scenario. Specifically, we study the overall performance (F1 Macro and WER) and subgroup performance in terms of average divergence of the top-10 subgroup with lower performance than the average (Δ^{-}_{avg-10}) and the average

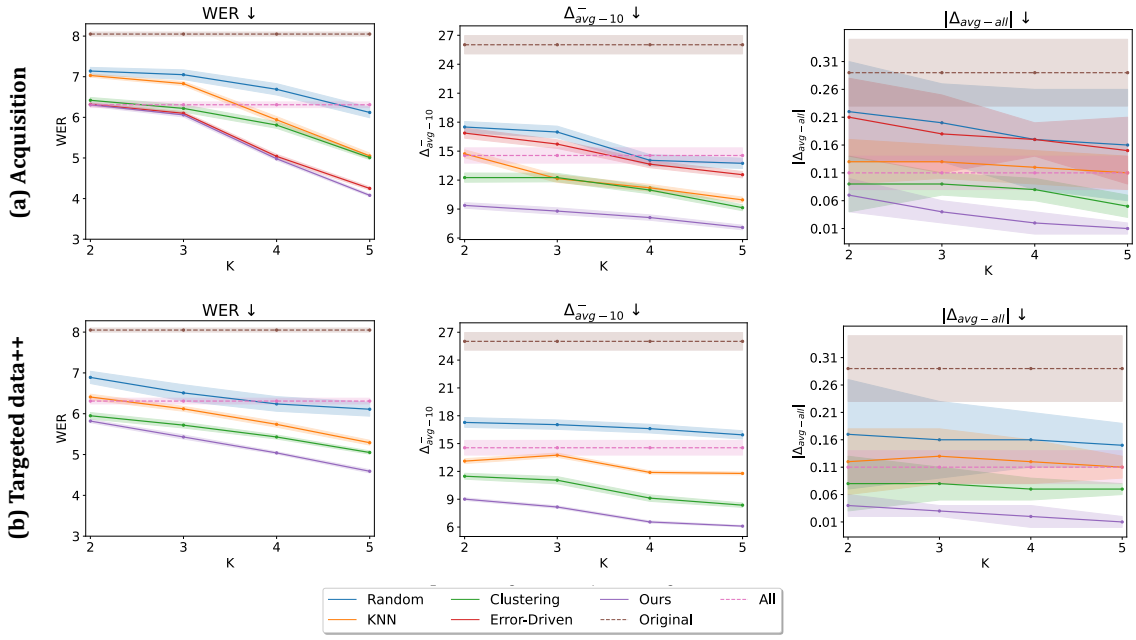


Fig. 3. **Sensitivity Analysis on K - LIBRISPEECH dataset**. WER (left), Δ^{-}_{avg-10} (middle), and $|\Delta_{avg-all}|$ (right) for the considered approaches in (a) the post-processing acquisition (up) and (b) in-processing targeted data augmentation (down) settings; Whisper base monolingual model.

absolute divergence across all subgroups ($|\Delta_{avg-all}|$). For the FSC dataset (Figures 2), for our approach, lower values of K correspond to higher overall performance. Intuitively, we let the model prioritize addressing the subgroups where it underperforms the most, resulting in the highest performance improvement. Similarly, lower values of K reduce the average subgroup divergence Δ^{-}_{avg-10} as we again let the model focus more on a few challenging subgroups. Conversely, as we increase K, we decrease the $|\Delta_{avg-all}|$. This outcome indicates that by targeting a broader range of subgroups for mitigation, the model can address a wider range of subgroup behavior.

On the other hand, for the LIBRISPEECH dataset, all evaluated mitigation approaches achieve better performance (i.e., lower WER) when increasing K. We attribute this difference to the nature of the tasks and datasets. The ASR task on the LIBRISPEECH dataset is a more complex task than IC on FSC, which instead involves fixed intent classification classes. By increasing K, we incorporate data from a broader set of subgroups with varied characteristics, which enhances data heterogeneity. This diversity benefits ASR performance, allowing the model to generalize better. This consideration also applies at the subgroup level for the top 10 most divergent subgroups. Finally, similarly to FSC, we observe that increasing K also reduces the average absolute divergence across all groups $|\Delta_{avg-all}|$, allowing the model to address divergences across more subgroups. Interestingly, the results exhibit a high variability across the three runs (i.e., high standard deviation) for most of the evaluated baselines, except for the clustering-based mitigation approach. Both our approach and the clustering-based one show more stable outcomes, suggesting that directly mitigating at the subgroup level – whether through patterns (as in our method) or clusters– is better suited for addressing subgroup disparities effectively.

The divergence-aware regularization does not depend on the parameter K. Hence, not only allows to achieve the best results generally, but it does not need this parameter setting. This regularization thus stands as a more suitable and suggested in-processing technique than divergence-aware data augmentation.

C. Joint adoption of mitigation strategies

We investigate whether combining our three mitigation strategies could offer a complementary approach to further enhance model and subgroup performance. Each mitigation method addresses subgroup disparities from a different perspective. Data acquisition enriches the training set with underperforming samples, regularization directly targets subgroup divergence within the model's learning process, and augmentation improves the model robustness at the subgroup level by synthetically expanding subgroup representation.

We evaluate all possible combined strategies and assess their complementary effects on the FSC dataset. Specifically, we consider (i) divergence-aware regularization and data augmentation, (ii) data augmentation and data acquisition, (iii) regularization and data acquisition, and (iv) the combination of all three approaches. We first adopt the in-processing technique(s), followed by the post-processing data acquisition. We report the mitigation results in Table IV.

Regularization + data acquisition is the most effective when coupling two strategies, demonstrating the benefit of integrating complementary approaches. After refining the model at the subgroup level through regularization, the acquisition of additional challenging samples provides a more diverse representation of the subgroups, thus further improving the

TABLE IV
JOINT ADOPTION OF THE MITIGATION STRATEGIES. MITIGATION RESULTS WHEN COMBINING THE PROPOSED MITIGATION STRATEGIES, INCLUDING TARGET DATA AUGMENTATION, REGULARIZATION AND DATA ACQUISITION; FSC DATASET.

Strategy	*Accuracy*	*F1 Macro*	Δ^-_{max}	Δ^-_{avg-10}	Δ^-_{avg-20}	Δ^-_{avg-50}	$\lvert\Delta_{avg-all}\rvert$
original	91.58±0.08	86.34±0.13	-70.09±0.26	-70.09±0.26	-65.73±0.49	-53.31±0.19	1.06±0.07
acquisition	96.55±0.08	94.71±0.12	-40.60±0.35	-40.28±0.36	-38.08±0.36	-32.72±0.28	0.81±0.03
target data++	95.75±0.37	95.48±0.35	-36.12±0.39	-35.98±0.37	-34.77±0.36	-32.65±0.33	0.35±0.04
regularization	96.47±0.11	96.33±0.12	-34.49±0.45	-34.49±0.45	-34.11±0.41	-31.34±0.32	0.29±0.01
regularization & acquisition	**97.04±0.09**	96.89±0.10	-33.15±0.31	-33.12±0.29	**-32.78±0.23**	**-30.07±0.21**	0.31±0.02
target data++ & acquisition	96.47±0.15	95.83±0.13	-36.14±0.36	-36.14±0.36	-35.95±0.33	-32.29±0.28	0.34±0.02
regularization & target data++	96.51±0.20	96.40±0.14	-34.12±0.38	-34.10±0.38	-33.97±0.34	-30.62±0.25	0.27±0.01
regularization & target data++ & acquisition	97.03±0.05	**96.91±0.04**	**-33.10±0.12**	**-33.10±0.12**	-32.82±0.09	-30.38±0.06	**0.25±0.01**
all data	93.42±0.17	93.11±0.17	-53.18±0.15	-50.89±0.09	-45.61±0.14	-40.37±0.16	0.37±0.01

performance compared to individual adoption. Combining the two in-processing techniques slightly outperforms their individual use, but it is less effective than regularization + data acquisition. Both methods operate by boosting subgroup performance starting from the same training data, indicating that their combined benefits may be limited. Finally, the combination of the three approaches yields comparable results to the regularization + data acquisition alone. While some metrics show improved performance, others do not reach the same level. Overall, the findings suggest that combining multiple strategies can be beneficial, especially the integration of the complementary regularization + data acquisition ones.

D. Discussion

Our findings demonstrate the effectiveness of our post-processing and in-processing techniques in addressing subgroup performance disparities and improving overall performance. In- and post-processing methods offer distinctive advantages and are suited for diverse application scenarios.

Post-processing data acquisition is particularly beneficial when practitioners have an existing trained model and can obtain additional data to enhance subgroup representation. In scenarios with sufficient budget, access to data sources, or the ability to collect data, this technique enables users to identify and target underperforming subgroups to enhance model performance. However, it may be less effective in cases with limited data availability or budget constraints, as it can be difficult to gather enough relevant samples under such conditions.

In-processing techniques overcome the need to acquire additional data, as they address subgroup disparities during training. These solutions allow for a more flexible mitigation by working with available data. Yet, they operate during the model development phase and do not improve already trained ones. Our results show that divergence-aware regularization, in particular, significantly improves model performance, making it well-suited for applications where data access is limited as in our experiments.

VI. CONCLUSIONS

This study addresses the critical aspect of mitigating disparities in performance across different population subgroups by proposing a divergence-aware dual mitigation strategy. Our approach automatically identifies subgroups showing a worse performance compared to the overall model behavior and addresses such disparate treatment. We propose both a post-processing method and two in-processing approaches, thus offering versatility and adaptability to diverse real-world scenarios. The post-processing technique mitigates biases of an already trained model by acquiring data samples from underperforming subgroups thanks to their interpretable representation. The in-processing methods address biases during the training itself, and we proposed both targeted data augmentation and divergence-aware regularization. Our experimental results show the effectiveness of post-processing targeted sample acquisition in enhancing subgroups and overall model performance of trained models compared to existing baselines. Notably, the in-processing methods show the best results in reducing disparities, with regularization slightly outperforming subgroup-based data augmentation. Our paper offers a comprehensive framework for addressing subgroup disparities at two critical stages of model development, during training and post-training adjustment, offering practitioners versatile tools to mitigate speech model biases.

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