PERSONALIZING ASR WITH LIMITED DATA USING TARGETED SUBSET SELECTION

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ABSTRACT

We study the task of personalizing ASR models to a target non-native speaker/accent while being constrained by a transcription budget on the duration of utterances selected from a large unlabelled corpus. We propose a subset selection approach using the recently proposed submodular mutual information functions, in which we identify a diverse set of utterances that match the target speaker/accent. This is specified through a few target utterances and achieved by modelling the relationship between the target subset and the selected subset using submodular mutual information functions. This method is applied at both the speaker and accent levels. We personalize the model by fine tuning it with utterances selected and transcribed from the unlabelled corpus. Our method is able to consistently identify utterances from the target speaker/accent using just speech features. We show that the targeted subset selection approach improves upon random sampling by as much as 2% to 5% (absolute) depending on the speaker and accent and is 2x to 4x more label-efficient compared to random sampling. We also compare with a skyline where we specifically pick from the target and our method generally outperforms the oracle in its selections.

Index Terms— Personalization, Data Selection, Accent and Speaker Adaptation, Submodular Mutual Information

1. INTRODUCTION

State-of-the-art speech recognition systems have seen tremendous progress in the last few years, with end-to-end architectures becoming a default modeling choice. While end-to-end models yield impressive WER reductions and work well for certain user populations [1, 2], they severely underperform when confronted with out-of-domain test utterances in target accents that are unseen or rarely seen during training. A common solution to address such mismatched settings is to adapt a well-trained, speaker-independent ASR model with a small amount of target-specific data to build personalized models for each target setting. Prior work on personalizing end-to-end models proposes finetuning pre-trained ASR models using small amounts of speaker-specific utterances [3, 4]. While these works propose different finetuning schedules that would be most beneficial given the limited amount of target data, the question of which speaker-specific utterances should be chosen in order to be transcribed and further used for finetuning has received far less attention. [5] presents a method to select sentences within a fixed budget that are most likely to induce ASR errors and result in higher-quality personalized ASR models for target accents compared to random selection. However, they assume access to a small seed set of labeled utterances from the target speaker. We address the more realistic setting where we have access only to a limited number of unlabeled utterances from the target setting.

In this work, we propose a targeted subset selection approach that makes use of a suite of submodular mutual information (SMI) functions optimizing different objective functions (originally defined in [6]). For a specific target speaker or a target accent, given access to a few speech utterances, we aim at identifying the most informative subset of speech utterances from a larger unlabeled pool that best matches the target set. Here, the best match is characterized by the underlying criteria of SMI functions, that makes use of pairwise similarities between speech representations. We find this to be an effective targeted subset selection technique for personalizing ASR models in two settings, one involving a specific target speaker and the other involving a specific target accent spanning multiple speakers. Our proposed technique uses much less budgets: as low as 25% of that of random. It also results in better fine-tuning of the ASR than an oracle system that chooses a subset assuming access to information about the target speaker/accent.

2. RELATED WORK

A number of works have studied subset selection for speech recognition. [7] and [8] use submodular functions for selecting subsets of speech utterances for speeding up and reducing the amount of labeled data required for ASR training. Similarly, [9] study subset selection to obtain low-vocabulary speech corpora for ASR, while [10] uses submodular approaches for targeted selection in machine translation. Many
recent papers [11, 12] have studied uncertainty and gradient based approaches for active learning to reduce the transcription time for ASR models, while [13] uses a committee-based active learning method to select speech utterances.

A number of approaches have studied personalized speech recognition, such as for dysarthric and accented speech [3] by finetuning a subset of layers using labelled data of targeted accents or accent adaptation [14] using labelled data for the target accent. [15] personalizes ASR on-device using RNN Transducers. [5] works on a problem that corresponds exactly to the reverse of our setting by trying to determine the most error-prone sentences for the model to record utterances on. While this can be effective for user-driven personalization, our method is suited for when we have fixed speech utterances and the only actionable item for us is to transcribe a subset of them.

Finally, a number of recent works have leveraged the submodular mutual information functions (used in this work) for targeted selection. [16] use the SMI functions for query focused and privacy-preserving summarization, while [17] uses the SMI functions for improving the model performance on targeted slices. Recently, [18] proposed an active learning approach using the SMI functions for rare classes, redundacy, and OOD data.

3. SUBMODULAR MUTUAL INFORMATION (SMI) FUNCTIONS

Submodular Functions: We let $\mathcal{V}$ denote the ground-set of $n$ data points $\mathcal{V} = \{1, 2, 3, \ldots, n\}$ and a set function $f : 2^\mathcal{V} \rightarrow \mathbb{R}$. The function $f$ is submodular [19] if it satisfies the diminishing marginal returns, namely $f(j | \mathcal{X}) = f(\mathcal{X} \cup j) - f(\mathcal{X}) \geq f(j | \mathcal{Y})$ for all $\mathcal{X} \subseteq \mathcal{Y} \subseteq \mathcal{V}, j \notin \mathcal{Y}$. Submodularity ensures that a greedy algorithm achieves bounded approximation factor when maximized [20].

Submodular Mutual Information (SMI): Given a set of items $\mathcal{S}, \mathcal{T} \subseteq \mathcal{V}$, the submodular mutual information (MI) [21, 6] is defined as $I_f(\mathcal{S}; \mathcal{T}) = f(\mathcal{S}) + f(\mathcal{T}) - f(\mathcal{S} \cup \mathcal{T})$. Intuitively, this measures the similarity between $\mathcal{T}$ and $\mathcal{S}$ and we refer to $\mathcal{T}$ as the targeted set. In the setting considered in this paper, the set $\mathcal{T}$ (target set) comprises of a small set of unlabeled utterances of a speaker or an accent, and $\mathcal{V}$ is a large unlabeled set of utterances of multiple speakers and accents. To find an optimal subset given a target set $\mathcal{T}$, we can define $g_T(\mathcal{S}) = I_f(\mathcal{S}; \mathcal{T})$, $\mathcal{S} \subseteq \mathcal{V}$ and maximize the same. With a greedy algorithm, these submodular functions can be efficiently optimized within a minimum bound $(1-1/e)$ fraction of the global maximum.

3.1. Examples of SMI functions

We use the MI functions recently introduced in [6] and their extensions introduced in [16, 17]. For any two data points $i \in \mathcal{V}$ and $j \in \mathcal{T}$, let $s_{ij}$ denote the similarity between them.

Graph Cut MI: The submodular mutual information (SMI) instantiation of graph-cut (GCMI) is defined as [17, 6]:

$$I_f(\mathcal{S}; \mathcal{T}) = 2 \sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{T}} s_{ij}$$

Since maximizing GCMI maximizes the joint pairwise sum with the query set, it will lead to a summary similar to the query set $\mathcal{Q}$. GCMI models only query-relevance and does not select based on diversity [17].

Facility Location MI: The Facility Location Mutual Information (FLMI) function [17] takes the expression:

$$I_f(\mathcal{S}; \mathcal{T}) = \sum_{i \in \mathcal{S}} \max_{j \in \mathcal{T}} s_{ij} + \sum_{i \in \mathcal{T}} \max_{j \in \mathcal{S}} s_{ij}$$

FLMI is very intuitive for query relevance as well. It measures the similarity between representation of data points that are the most relevant to the query set, and vice versa.

Log Determinant MI: The SMI instantiation of logDMI can be defined as [17]:

$$I_f(\mathcal{S}; \mathcal{T}) = \log \det(\mathcal{S}) - \log \det(\mathcal{S} - \mathcal{S}_T \mathcal{S}_T^{-1} \mathcal{S}_S^{\top})$$

$\mathcal{S}_S, \mathcal{T}$ denotes the cross-similarity matrix between the items in sets $\mathcal{S}$ and $\mathcal{T}$ and $\mathcal{S}_S$ denotes the similarity sub-matrix with rows and columns from the set $\mathcal{S}$. This function provides a trade-off between query-relevance and diversity.

4. OUR ALGORITHM

Setting: We are provided a few unlabeled utterances of the speaker/accent (a target set $\mathcal{T}$) which we would like the ASR model $M$ to be personalized to. This target set is either a specific speaker or a specific accent.

Goal: The goal of the paper is to select the most informative subset $\mathcal{S}$ w.r.t. target $\mathcal{T}$ from a large corpus $\mathcal{V}$ of unlabeled data, called the ground set. We are given a budget constraint, which is a constraint on the total time of the selected utterances. This corresponds to the transcription budget, since the selected utterances need to be later transcribed by a human.

Approach: The approach is outlined in Alg. 1. The first step is to define the SMI functions. The SMI functions are defined by computing a euclidean similarity kernel $s_{ij}$ on the MFCC features of the utterances. Specifically, we set $s_{ij} = \exp(-||\text{mfcc}_i - \text{mfcc}_j||^2)$ where $\text{mfcc}_1, \text{mfcc}_2$ are the MFCC features of utterances $i, j$. Using the SMI functions defined above, we select a subset that maximizes $g_T(\mathcal{S}) = I_f(\mathcal{S}; \mathcal{T})$ for the given targeted set of utterances $\mathcal{T}$. Specifically, we optimize $g_T(\mathcal{S}) = I_f(\mathcal{S}; \mathcal{T})$ subject to the constraint $c(\mathcal{S}) \leq B$, where $B$ is the transcription budget.
where \(c\) corresponds to the time (in seconds) of the specific utterance and \(B\) is the time budget. We use the greedy algorithm \([20][22]\) with a knapsack constraint for optimizing, where specifically given the current set \(S\), we select the item \(i = \arg \max_{j \in \mathcal{V} \setminus S} g_T(j; S)\), with the stopping criterion as \(c(S) \leq B\). Once, we obtain the set \(\hat{S}\) as the solution of this optimization problem, we obtain the transcriptions from a human, and finetune the ASR model on the utterances in \(\hat{S}\).

**Algorithm 1: Personalizing ASR model \(M\)**

\[
\begin{align*}
\textbf{Require:} & \quad \text{target } T, \text{ budget } B, \text{ SMI function type } f \\
\textbf{Data:} & \quad \text{large unlabelled ground set } \mathcal{V} \\
1 & \quad \text{Define an SMI function } g_T(S) = I_f(S; T) \text{ using} \\
2 & \quad \text{Gaussian kernel similarity with the MFCC features} \\
3 & \quad \hat{S} \leftarrow \arg \max_{S \subseteq \mathcal{V}, c(S) \leq B} g_T(S) \\
4 & \quad D \leftarrow \text{Transcribe utterances in } \hat{S} \\
5 & \quad \text{Fine-tune ASR model } M \text{ on } D
\end{align*}
\]

5. EXPERIMENTAL SETUP

**Tasks:** We experiment with personalizing ASR models in two settings: 1. The target set comes from a specific speaker, and 2. The target set comes from a specific accent.

**Datasets:** We report results on two public datasets, viz., L2-Arctic and IndicTTS, containing English speech in non-native accents. L2-Arctic has English speech from 24 speakers spanning six non-native accents: Hindi (HIN), Vietnamese (VTN), Chinese (CHN), Korean (KOR), Arabic (ARB) and Spanish (ESP). IndicTTS consists of speech from 8 Indian speakers, each with a different accent depending on their native language: Kannada (Kn), Tamil (Ta), Malayalam (MI), Hindi (Hi), Rajasthani (Ra), Assamese (As) and Manipuri (Ma). For each target speaker and accent, we created data splits by partitioning 70% of the data into a ground set (\(\mathcal{V}\)) and a very small target set \(T\) (with sizes varying from 10 to 50) and we created test/development sets from the remaining 30% using a 27/3 split, respectively. For L2-Arctic, the test sets for a target speaker and a target accent contained roughly 300 utterances and 1.2K utterances, respectively. When grouped by target speakers, \(|\mathcal{V}| \approx 740\), and for a specific target accent, \(|\mathcal{V}| \approx 3000\). For IndicTTS, the average sizes of the ground set and the test set are 4.3K and 1.9K utterances respectively. Given that this dataset contains speech from only one speaker per accent, it was not used for accent personalization.

**Features.** We represent each utterance as a 39-dimensional feature vector of MFCC coefficients averaged over the duration of the utterance. Fig. 1 shows a t-SNE plot of MFCC features of IndicTTS test set utterances coloured using speaker IDs. We observe good speaker-specific clusters that are well-separated from each other.

**ASR Models:** Following [5], our pre-trained model is based on the QuartzNet-15x5 [23] architecture. It is trained on LibriSpeech [24] for 400 epochs using the CTC-loss [25] and yields a WER of 3.90 on the test-clean split of LibriSpeech. The QuartzNet-15x5 architecture is fully convolutional with residual connections. This model is finetuned with our selected subsets of accented speech to minimize CTC loss using the NovoGrad optimizer [26] for 100 epochs with a batch size of 16, a linearly decaying learning rate of \(10^{-5}\) and early stopping based on the dev set. In all our experiments, we report results averaged over three runs using three different seeds.

6. EXPERIMENTS AND RESULTS

We experiment with personalized ASR systems for a specific target speaker and a specific target accent. For each setting, we compare the following approaches: (i) random selection (baseline), (ii) SMI-based selection using three SMI functions, FLMI, GCMI and LogDMI and (iii) a skyline oracle system that uses the speaker/accent metadata and randomly samples from the targeted accent/speaker. Unless specified otherwise, we use target sets of size 10 and a transcription budget of 360 sec for L2-Arctic and 492 sec for IndicTTS, amounting to an average of 100 utterances in each dataset.

| Accent   | Pre-train | Random | FLMI  | GCMI  | LogDMI | Skyline |
|----------|-----------|--------|-------|-------|--------|---------|
| arabic   | 24.29     | 23.96  | 22.38 | 22.49 | 22.08  | 22.05   |
| hindi    | 18.05     | 17.58  | 15.47 | 16.58 | 16.26  | 16.15   |
| chinese  | 30.66     | 29.19  | 27.51 | 27.78 | 27.87  | 27.91   |
| korean   | 19.05     | 18.06  | 17.08 | 18.45 | 18.45  | 17.18   |
| spanish  | 23.44     | 22.97  | 21.92 | 22.32 | 21.96  | 22.39   |
| vietnamese| 37.03     | 35.37  | 33.10 | 33.20 | 32.78  | 33.2    |

**Table 1:** Accent personalisation in L2-Arctic (\(B = 360s\))
When personalizing to a target speaker under a limited budget, GCMI largely selects from the target speaker (given its objective which does not explicitly reward diversity) unlike in the target accent setting.

Rankings among SMI functions based on WER reductions are less consistent when the budgets are increased, as seen in Fig. 2 that shows the WER improvements using GCMI, FLMI and LogDMI for a specific accent (Chinese) and target speaker (Assamese female) by varying durations of the selected subsets. However, they always consistently outperform random selection. For Chinese-accented English, we observe that FLMI yields a WER reduction of 3.15 with 6 minutes of data, while a similar reduction needs 24 minutes using random selection.

### 7. CONCLUSION

In this work, we propose a targeted subset selection approach using submodular mutual information functions that help identify speech utterances that best match an unlabeled target set of limited size. We evaluate our approach by limiting the target set to either a single speaker or a single accent. Our method consistently outperforms random selection methods and even beats an oracle system when the target set is from a specific accent. Future work will explore extensions of this approach to adapt to speakers with speech impediments.
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