ASR for Under-Resourced Languages from Probabilistic Transcription

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Abstract

In many under-resourced languages it is possible to find text, and it is possible to find speech, but transcribed speech suitable for training automatic speech recognition (ASR) is unavailable. In the absence of native transcripts, this paper proposes the use of a probabilistic transcript: a probability mass function over possible phonetic transcripts of the waveform. Three sources of probabilistic transcripts are demonstrated. First, self-training is a well-established semi-supervised learning technique, in which a cross-lingual ASR first labels unlabeled speech, and is then adapted using the same labels. Second, mismatched crowdsourcing is a recent technique in which non-speakers of the language are asked to write what they hear, and their nonsense transcripts are decoded using noisy channel models of second-language speech perception. Third, EEG distribution coding is a new technique in which non-speakers of the language listen to it, and their electrocortical response signals are interpreted to indicate probabilities. ASR was trained in four languages without native transcripts. Adaptation using mismatched crowdsourcing significantly outperformed self-training, and both significantly outperformed a cross-lingual baseline. EEG distribution coding and text-derived phone language models were both shown to improve the quality of probabilistic transcripts derived from mismatched crowdsourcing.

Index Terms

Automatic speech recognition, Under-resourced languages, Mismatched crowdsourcing, EEG

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I. Introduction

Automatic speech recognition (ASR) has the potential to provide database access, simultaneous translation, and text/voice messaging services to anybody, in any language, dramatically reducing linguistic barriers to economic success. To date, ASR has failed to achieve its potential, because successful ASR requires very large labeled corpora. Current methods require about 1000 hours of transcribed speech per language, transcribed at a cost of about 6000 hours of human labor; the human transcribers must be computer-literate, and they must be native speakers of the language being transcribed. In many languages, recruiting dozens of computer-literate native speakers is impractical.

Instead of recruiting native transcribers in search of a perfect reference transcript, this paper proposes the use of probabilistic transcripts. A probabilistic transcript is a probability mass function, $\rho_\Phi(\phi)$, specifying, as a real number between 0 and 1, the probability that any particular phonetic transcript ϕ is the correct transcript of the utterance. Prior to this work, machine learning has almost always assumed that the training dataset contains either deterministic transcripts ($\rho_{DT}(\phi) \in \{0, 1\}$, commonly called "supervised training") or completely untranscribed utterances (commonly called "unsupervised training," in which case we assume that $\rho_{LM}(\phi)$ is given by some *a priori* language model). This article proposes that, even in the absence of a deterministic transcript, there may be auxiliary sources of information that can be compiled to create a probabilistic transcript with entropy lower than that of the language model, and that machine learning methods applied to the probabilistic transcript are able to make use of its reduced entropy in order to learn a better ASR. In particular, this paper considers three useful auxiliary sources of information:

1) SELF-TRAINING: ASR pre-trained in other languages is used to transcribe unlabeled training data in the target language.
2) MISMATCHED CROWDSOURCING: Human crowd workers who don't speak the target language are asked to transcribe it as if it were a sequence of nonsense syllables.
3) EEG DISTRIBUTION CODING: Humans who do not speak the target language are asked to listen to its extracted syllables, and their EEG responses are interpreted as a probability mass function over possible phonetic transcripts.

II. Background

Suppose we require that, in order to develop speech technology, it is necessary first to have (1) some amount of recorded speech audio, and (2) some amount of text written in the target language. These two requirements can be met by at least several hundred languages: speech audio can be recorded from podcasts or radio broadcasts, and text can be acquired from Wikipedia, Bibles, and textbooks. Recorded speech is, however, not usually transcribed; and the requirement of native language transcription is beyond the economic capabilities of many minority-language communities.

A. ASR in Under-Resourced Languages

Krauwer [25] defined an under-resourced language to be one that lacks one or more of: stable orthography, significant presence on the internet, linguistic expertise, monolingual tagged corpora, bilingual electronic dictionaries, transcribed speech, pronunciation dictionaries, or other similar electronic resources. Berment [3] defined a rubric for tabulating the resources available in any given language, and proposed that a language should be called "under-resourced" if it scored lower than 10.0/20.0 on the proposed rubric. By these standards, technology for under-resourced languages is most often demonstrated on languages that are not really under-resourced: for example, ASR may be trained without transcribed speech, but the quality of the resulting ASR can only be proven by measuring its phone error rate (PER) or word error rate (WER) using transcribed speech. The intention, in most cases, is to create methods that can later be ported to truly under-resourced languages.

The International Phonetic Alphabet (IPA [19]) is a set of symbols representing speech sounds (phones) defined by the principle that, if two phones are used in any language to make meaningful linguistic contrasts (i.e., they represent distinct phonemes), then those phones should have distinct symbolic representations in the IPA. This makes the IPA a natural choice for transcripts used to train cross-language ASR systems, and indeed ASR in a new language can be rapidly deployed using acoustic models trained to represent every distinct symbol in the IPA [37]. However, because IPA symbols are defined phonemically, there is no guarantee of cross-language equivalence in the acoustic properties of the phones they represent. This problem arises even between dialects of the same language: a monolingual Gaussian mixture model (GMM) trained on five hours of Levantine Arabic can be improved by adding ten hours of Standard Arabic data, but only if the log likelihood of cross-dialect data is scaled by 0.02 [16].

Better cross-language transfer of acoustic models can be achieved, but only by using structured transfer learning methods, including neural networks (NN) and subspace Gaussian mixture models (SGMM). SGMMs use language-dependent GMMs, each of which is the linear interpolation of language-independent

mean and variance vectors [35], e.g., 16% relative WER reduction was achieved in Tamil by combining SGMM with an acoustic data normalization technique [30]. NN transfer learning can be categorized as tandem, bottleneck, pre-training, phone mapping, and multi-softmax methods. In a tandem system, outputs of the NN are Gaussianized, and used as features whose likelihood is computed with a GMM; in a bottleneck system, features are extracted from a hidden layer rather than the output layer. Both tandem [42] and bottleneck [45] features trained on other languages can be combined with GMMs [45] or SGMMs [18] trained on the target language in order to improve WER.

A hybrid ASR is a system in which the NN terminates in a softmax layer, whose outputs are interpreted as phone or senone [7] probabilities. Knowledge of the target language phone inventory is necessary to train a hybrid ASR, but it is possible to reduce WER by first pre-training the NN hidden layers with multilingual data [15], [43]. A hybrid ASR can be constructed using very little in-language speech data by adding a single phone-mapping layer [40] or senone-mapping layer [10] to the output of the multilingual NN. A multi-softmax system is a network with several different language-dependent softmax layers, each of which is the linear transform of a multilingual shared hidden layer [15], [36], [45].

B. Self-Training

Self-training is a class of semi-supervised learning techniques in which a classifier labels unlabeled data, and is then re-trained using its own labels as targets. Self-training is frequently used to adapt ASR from a well-resourced language to an under-resourced language [28], [5], or in some cases, to create target-language ASR by adapting several source-language ASRs [46]. A self-trained classifier tends to be too conservative, because the tails of the data distribution are truncated by the self-labeling process [38]; on the other hand, a self-trained classifier needs to be conservative, because the error rate of the learned classifier increases at a rate more than proportional to the error rate of the self-labeling process [17]. Self-training is therefore most useful when the in-language training data are filtered, to exclude frames with confidence below a threshold [44], and/or weighted, so that some frames are allowed to influence the learned parameters more than others [14]. Self-training of NN systems has been shown to be about 50% more effective (1.5 times the error rate reduction) as self-training of GMM systems [17].

C. Mismatched Crowdsourcing

In [22], a methodology was proposed that bypasses the need for native language transcription: mismatched crowdsourcing sends target language speech to crowd-worker transcribers who have no knowledge of the target language, then uses explicit mathematical models of second language phonetic perception to recover an equivalent phonetic transcript (Fig. 1). Majority voting is re-cast, in this paradigm, as a

form of error-correcting code (redundancy coding), which effectively increases the capacity of the noisy channel; interpretation as a noisy channel permits us to explore more effective and efficient forms of error-correcting codes. Assume that cross-language phone misperception is a finite-memory process, and can therefore be modeled by a finite state transducer (FST). The complete sequence of representations from utterance language to annotation language can therefore be modeled as a noisy channel represented by the composition of up to three consecutive FSTs (Fig. 1): a pronunciation model, a misperception model, and an inverted grapheme-to-phoneme (G2P) transducer.

D. Electrophysiology of Speech Perception

The human auditory system is sensitive to within-category distinctions in speech sounds, but such pre-categorical perceptual distinctions may be lost in transcription tasks, where listeners must filter their percepts through the limited number of categorical representations available in their native language orthography. EEG distribution coding is a proposed new method that interprets the electrical evoked potentials of untrained listeners (measured by electroencephalography or EEG) as a probability distribution over the phone set of the utterance language (Fig. 2). Transcribers, in this scenario, listen to speech in both their native language and an unfamiliar non-native target language, while their EEG responses are recorded. From their responses to English speech, an English-language EEG phone recognizer is trained [9]. Misperception probabilities $\rho(\psi|\phi)$ are then estimated: for each non-native phone ϕ, the classifier outputs are interpreted as an estimate of $\rho(\psi|\phi)$.

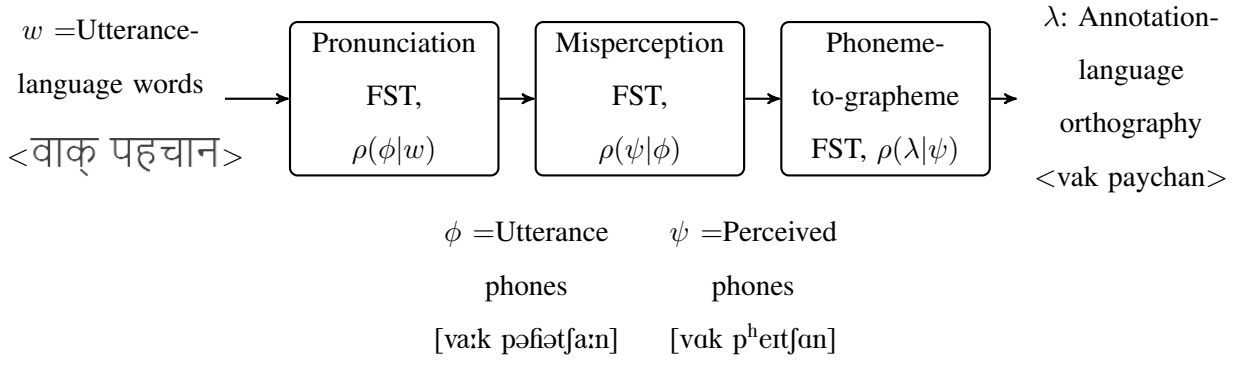


Fig. 1. Mismatched Crowdsourcing: crowd workers on the web are asked to transcribe speech in a language they do not know. Annotation mistakes are modeled by a finite state transducer (FST) model of utterance-language pronunciation variability (reduction and coarticulation), composed with an FST model of non-native speech misperception (mapping utterance-language phones to annotation-language phones), composed with an inverted grapheme-to-phoneme (G2P) transducer.

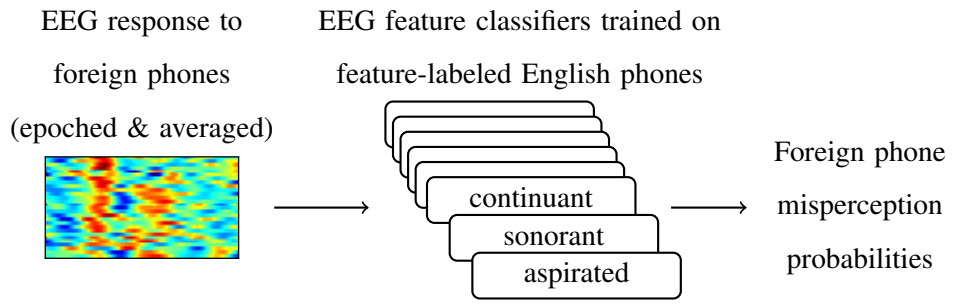


Fig. 2. EEG responses are recorded while listeners hear speech in their native language. For each listener, a bank of distinctive feature classifiers are trained. Listeners then hear speech in an unfamiliar language, and their EEG responses are classified, estimating a listener-language probabilistic transcript of the non-native speech.

III. Algorithms that Induce a Probabilistic Transcript

A deterministic transcript is a sequence of phone symbols, $\phi^\ell = [\phi^\ell_1, \ldots, \phi^\ell_M]$ where ϕ^ℓ_m is a symbol drawn from the phone set of the utterance language.

A probabilistic transcript is a probability mass function (pmf) over the set of deterministic transcripts. Capital letters denote random variables, lowercase denote instances: Φ^ℓ_m is a random variable whose instance is ϕ^ℓ_m. Denote the probability of transcript ϕ^ℓ as $\rho_{\Phi^\ell}(\phi^\ell)$, where ρ ("reference") means that $\rho_{\Phi^\ell}(\phi^\ell)$ is a reference distribution—a distribution specified by the probabilistic transcription process, and not dependent on ASR parameters during training. The distribution label Φ^ℓ is omitted when clear from the instance label, e.g., $\rho(\phi^\ell)$, but $\rho_{\Phi^\ell}(u)$. Superscript denotes waveform index, while subscript denotes frame or phone index. Absence of either superscript or subscript denotes a collection, thus $\Phi = \{\Phi^1, \ldots, \Phi^L\}$ (with instance value $\phi = \{\phi^1, \ldots, \phi^L\}$) is the random variable over all transcripts of the database. In all of the work described in this paper, the probabilistic transcript is represented as a confusion network [29], meaning that it is the product of independent symbol pmfs $\rho(\phi^\ell_m)$:

$$\rho(\phi) = \prod_{\ell=1}^{L} \rho(\phi^\ell) = \prod_{\ell=1}^{L} \prod_{m=1}^{M} \rho(\phi^\ell_m) \tag{1}$$

The pmf $\rho(\phi^\ell)$ can be represented as a weighted finite state transducer (wFST) in which edges connect states in a strictly left-to-right fashion without skips, and in which the edges connecting state m to state $m+1$ are weighted according to the pmf $\rho(\phi^\ell_m)$ (Fig. 3).

Three different experimental sources were tested for the creation of a PT. Self-training is now well-established in the field of under-resourced ASR; we adopted the algorithm of Vesely, Hannemann and Burget [44]. Mismatched crowdsourcing used original annotations collected using published methods [23].

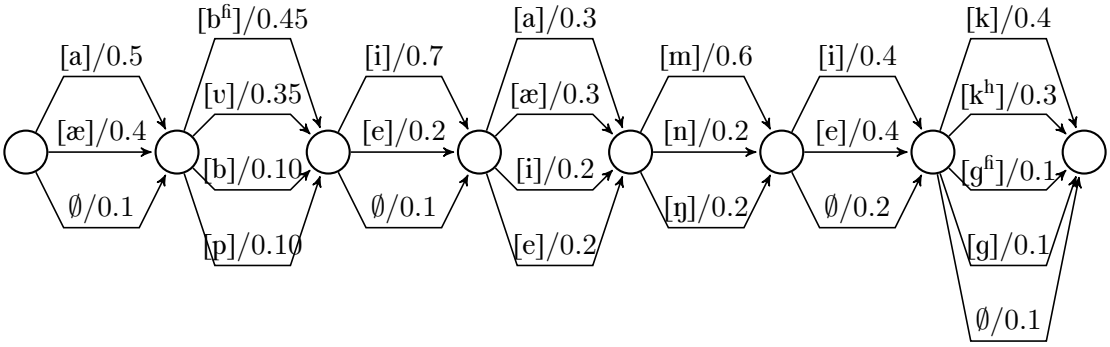


Fig. 3. A probabilistic transcript (PT) is a probability mass function (pmf) over candidate phonetic transcripts. All PTs considered in this paper can be expressed as confusion networks, thus, as sequential pmfs over the null-augmented space of IPA symbols. In this schematic example, $\emptyset$ is the null symbol, symbols in brackets are IPA, and numbers indicate probabilities.

EEG was not used independently here, but rather, was used to learn a misperception model applicable to the interpretation of mismatched crowdsourcing.

A. Self-Training

The first set of PTs is computed using NN self-training. The Kaldi toolkit [34] is first used to train a cross-lingual baseline ASR, using training data drawn from six languages not including the target language. The goal of self-training, then, is to adapt the NN to a database containing L speech waveforms in the target language, each represented by acoustic feature matrix $x^\ell = [x_1^\ell, \ldots, x_T^\ell]$, where x_t^ℓ is an acoustic feature vector. The feature matrix x^ℓ represents an utterance of an unknown phone transcript $\phi^\ell = [\phi_1^\ell, \ldots, \phi_M^\ell]$ which, if known, would determine the sequence but not the durations of senones (HMM states) $s^\ell = [s_1^\ell, \ldots, s_T^\ell]$.

The feature matrix x^ℓ is decoded using the cross-lingual baseline ASR, generating a phone lattice output. Using scripts provided by previous experiments [44], the phone lattice is interpreted as a set of posterior senone probabilities $\rho(s_t^\ell | x_t^\ell)$ for each frame, and the senone posteriors serve as targets for re-estimating the NN weights. Experiments using other datasets found that self-training should use best-path alignment to specify a binary target for NN training [44], but, apparently because of differences in the adaptation set between our experiments and previous work, we achieve better performance using real-valued targets.

B. Mismatched Crowdsourcing

The second set of PTs were computed by sending audio in the target language to non-speakers of the target language, and asking them to write what they hear. It would be preferable to recruit transcribers who speak a language with predictable orthography, but since transcribers in those languages were more expensive, this experiment instead recruited transcribers who speak American English. Denote using T the set of mismatched transcripts produced by these English-speaking crowd workers, which we wish to interpret as a pmf over target-language phone sequences, $\rho(\phi|T)$. As an intermediate step towards this goal, prior work [23] developed techniques to merge texts into a confusion network $\rho(\lambda|T)$ over representative transcripts in the annotation-language orthography (Fig. 4).

Once transcripts have been aligned and filtered to create the orthographic confusion network $\rho(\lambda|T)$, they are then translated into a distribution over phone transcripts according to:

$$\begin{aligned}\rho(\phi|T) &\approx \max_{\lambda} \rho(\phi|\lambda)\rho(\lambda|T) \\ &= \max_{\lambda} \left(\frac{\rho(\lambda|\phi)}{\rho(\lambda)} \rho(\phi) \right) \rho(\lambda|T) \end{aligned} \tag{2}$$

The terms other than $\rho(\lambda|T)$ in Equation (2) are estimated as follows. $\rho(\lambda)$ is modeled using a unigram prior over the letter sequences in λ. $\rho(\phi)$ is modeled using a bigram phone language model. $\rho(\lambda|\phi)$ is

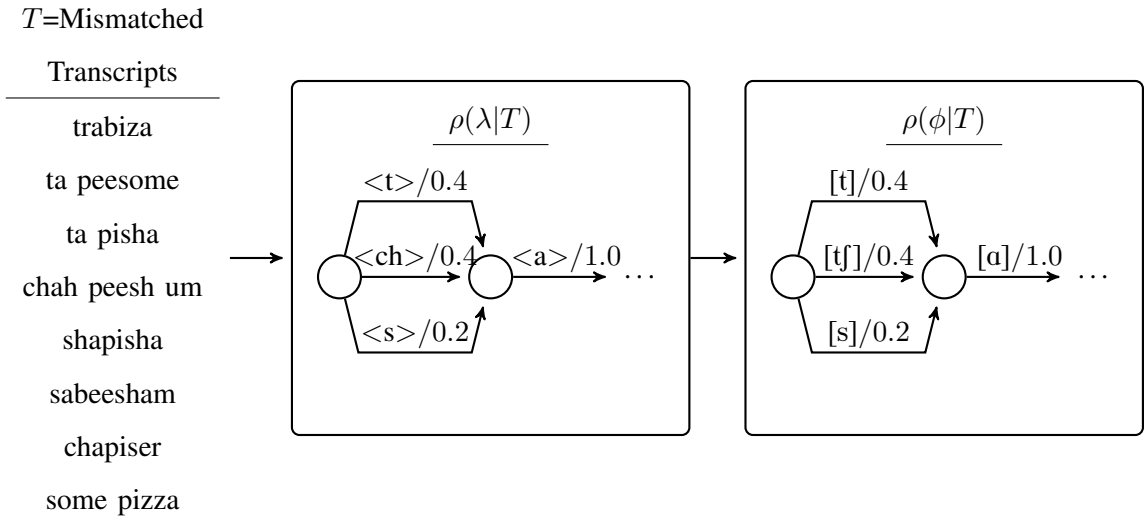


Fig. 4. Probabilistic transcription from mismatched crowdsourcing: Transcripts T are filtered to remove outliers, and merged to create a confusion network over orthographic symbols, $\rho(\lambda|T)$, from which the probabilistic transcript $\rho(\phi|T)$ is inferred. Example shown: Swahili speech, English-speaking transcribers. Symbols in <> are graphemes, symbols in [] are phones, numbers are probabilities.

called the misperception G2P, as it maps to graphemes in the annotation language, λ, from phones in the utterance language, ϕ. Section III-C describes methods that decompose $\rho(\lambda|\phi)$ into separate misperception and G2P transducers, but it can also be trained directly using representative transcripts λ (and their corresponding native transcripts) for speech *in languages other than the target language*. We assume that misperceptions depend more heavily on the annotation language than on the utterance language, and that therefore a model $\rho(\lambda|\phi)$ trained using a universal phone set for ϕ is also a good model of $\rho(\lambda|\phi)$ for the target language. Note that, while this assumption is not entirely accurate, it is necessitated by the requirement that no native transcripts in the target language can be used in building any part of our system.

C. Estimating Misperceptions from Electrocortical Responses

The misperception G2P described in Section III-B was estimated using a combination of mismatched and deterministic transcripts of non-target languages. However, with a small amount of transcribed data in the utterance language, it is possible to estimate the misperception G2P using electrocortical measurements of non-native speech perception. In this approach, the misperception G2P is decomposed into two separate transducers, a misperception transducer $\rho(\psi|\phi)$, and an annotation-language G2P $\rho(\lambda|\psi)$:

$$\rho(\lambda|\phi) \approx \sum_{\psi} \rho(\lambda|\psi)\rho(\psi|\phi) \tag{3}$$

where ϕ is a phone string in the utterance language, ψ is a phone string in the annotation language, and λ is an orthographic string in the annotation language. $\rho(\lambda|\psi)$ is an inverted G2P in the annotation language, e.g., trained on the CMU dictionary of American English pronunciations [26]. $\rho(\psi|\phi)$ is the mismatch transducer, specifying the probability that a phone string ϕ in the utterance language will be mis-heard as the annotation-language phone string ψ.

In principle, the mismatch transducer could be computed empirically from a phone confusion matrix, if experimental data on phone confusions were available for all phones in the target language, and those data were based on responses from listeners with the same language background as the crowd worker transcribers. These goals are hard to meet. An alternative is to use distinctive feature representations (originally proposed to characterize the perceptual and phonological natural classes of phonemes [20]) to predict misperceptions based on differences between the distinctive feature values of annotation- and utterance-language phones. Given the assumption that every distinctive feature shared by phones ϕ and ψ independently increases their confusion probability, their confusion probability can be expressed as

$$\rho(\psi|\phi) \propto \exp\left(-\sum_{k=1}^{K} w_k(\phi,\psi)\right) \tag{4}$$

where $w_k(\phi, \psi)$ is smaller if ϕ and ψ share the k^{th} distinctive feature. The assumption of independence is a simplifying assumption, given that many distinctive features have overlapping acoustic correlates. For example, the frequencies of the *two* lowest resonances of the vocal tract (the primary cues for vowel identity) are determined by articulatory gestures of the lips, jaw and tongue that are commonly represented by *three or more* distinctive features (e.g., height, backness, rounding, and advanced tongue root). Moreover, the weights w_k will probably also depend on properties of the speaker and listener (language, dialect, and idiolect), but data to train such a rich model do not exist.

However, a reasonable approximate model can be learned by assuming that w_k depend only on information about the listener, which can be incorporated via measurements of electrocortical activity. In particular, the weights w_k of the distinctive features can be set based on similarity of electrocortical responses (measured using EEG) as determined by a classifier trained to compute distinctive feature representations from electrocortical responses to the listener's native language phones. Thus, suppose a listener first hears phones $\phi = \psi$ in the native language, EEG response signals y are recorded, and a bank of binary classifiers $g_k(y)$ are trained to label the distinctive features $f_k(\phi)$ [9]. Second, the same listener hears phones $\phi \neq \psi$ in a new language, and EEG response signals y are recorded; then the contributions in Eq. (4) can be estimated as

$$w_k(\phi, \psi) = -\ln \Pr\left\{g_k(y) = f_k(\phi)\right\} \tag{5}$$

IV. Algorithms for Training ASR Using Probabilistic Transcription

An ASR is a parameterized pmf, $\pi(x, s|\phi, \theta)$, specifying the dependence of acoustic features, x, and senones, s, on the phone transcript ϕ and the parameter vector θ, where the notation $\pi(\cdot)$ denotes a pmf dependent on ASR parameters. Assume a hidden Markov model (HMM), therefore

$$\pi(x, s|\phi, \theta) = \prod_{\ell=1}^{L} \prod_{t=1}^{T} \pi(s_t^\ell | s_{t-1}^\ell, \phi^\ell, \theta) \pi(x_t^\ell | s_t^\ell, \theta)$$

A. Maximum Likelihood Training

Consider two observation-conditional sequence distributions $\pi(s, \phi|x, \theta)$ and $\pi(s, \phi|x, \theta')$, with parameter vectors θ and θ' respectively. The cross-entropy between these distributions is:

$$H\left(\theta \| \theta'\right) = -\sum_{s,\phi} \pi(s, \phi|x, \theta) \ln \pi(s, \phi|x, \theta') \tag{6}$$

$$= \mathcal{L}\left(\theta'\right) - Q\left(\theta, \theta'\right) \tag{7}$$

where the data log likelihood, $\mathcal{L}(\theta')$, and the expectation maximization (EM) quality function, $Q(\theta, \theta')$ [8], are defined by

$$\mathcal{L}\left(\theta'\right) = \ln \pi(x|\theta') \tag{8}$$

$$Q\left(\theta, \theta'\right) = \sum_{s,\phi} \pi(s, \phi|x, \theta) \ln \pi(x, s, \phi|\theta') \tag{9}$$

Cross-entropy is bounded below ($H(\theta\|\theta') \geq H(\theta\|\theta)$), therefore

$$\mathcal{L}\left(\theta'\right) - \mathcal{L}(\theta) \geq Q\left(\theta, \theta'\right) - Q(\theta, \theta) \tag{10}$$

Given any initial parameter vector θ_n, the EM algorithm finds $\theta_{n+1} = \text{argmax}_{\theta'} Q(\theta_n, \theta')$, thereby maximizing the minimum increment in $\mathcal{L}(\theta)$. For GMM-HMMs, the quality function $Q(\theta, \theta')$ is concave and can be analytically maximized; for NN-HMMs it is non-concave, but can be maximized using gradient ascent [2].

The probability $\pi(x, s, \phi|\theta)$ is computed by composing the following three weighted FSTs:

$$H : s^\ell \rightarrow s^\ell / \pi(x^\ell|s^\ell, \phi^\ell, \theta) \tag{11}$$

$$C : s^\ell \rightarrow \phi^\ell / \pi(s^\ell|\phi^\ell, \theta) \tag{12}$$

$$PT : \phi^\ell \rightarrow \phi^\ell / \rho(\phi^\ell) \tag{13}$$

where the notation has the following meaning. The probabilistic transcript, PT, is an FST that maps any phone string to itself. This mapping is deterministic and reflexive, but comes with a path cost determined by the transcription probability $\rho(\phi^\ell)$, as exemplified in Fig. 3. The context transducer, C, maps any senone sequence s^ℓ to a phone sequence ϕ^ℓ [31]. This mapping is stochastic, and the path cost is determined by the HMM transition weights

$$\pi(s^\ell|\phi, \theta) = \prod_{t=1}^{T} \pi(s_t^\ell|s_{t-1}^\ell, \phi^\ell, \theta) \tag{14}$$

The acoustic model, H, maps any senone sequence to itself. This mapping is deterministic and reflexive, but comes with a path cost determined by the acoustic modeling probability

$$\pi(x^\ell|s^\ell, \phi^\ell, \theta) = \prod_{t=1}^{T} \pi(x_t^\ell|s_t^\ell, \theta) \tag{15}$$

The posterior probability $\pi(s, \phi|x, \theta)$ is computed by composing the FSTs, pushing toward the initial state (normalizing so that probabilities sum to one), then finding the total cost of the path through $\text{PUSH}(H \circ C \circ PT)$ with input string s and output string ϕ. The analytical maximum of $Q(\theta, \theta')$ can be computed efficiently using the Baum-Welch algorithm, but experiments reported in this paper did not do so, for reasons described in the next subsection.

B. Segmental K-Means Training

The EM quality function, $Q(\theta, \theta')$, has properties that make it undesirable as an optimizer for $\mathcal{L}$. Suppose, as often happens, that there is a poor phone sequence, ϕ^p, that is highly unlikely given the correct parameter vector θ^*, meaning that $\pi(x, s, \phi^p|\theta^*)$ is very low. Suppose that the initial parameter vector, θ, is less discriminative, so that $\pi(x, s, \phi^p|\theta) > \pi(x, s, \phi^p|\theta^*)$. Indeed, the best speech recognizer is a parameter vector θ^* that completely rules out poor transcripts, setting $\pi(x, s, \phi^p|\theta^*) = 0$; but in this case $Q(\theta, \theta^*) = -\infty$. It is therefore not possible for the EM algorithm to start with parameters θ that allow ϕ^p, and to find parameters θ^* that rule out ϕ^p. With probabilistic transcription, this problem is quite common: if the human transcribers fail to rule out ϕ^p (e.g., because the correct and incorrect transcripts are perceptually indistinguishable in the language of the transcribers), then the EM algorithm will also never learn to rule out ϕ^p.

EM's inability to learn zero-valued probabilities can be ameliorated by using the segmental K-means algorithm [21], which bounds $\mathcal{L}(\theta')$ as $\mathcal{L}(\theta') \geq R(\theta, \theta')$:

$$R(\theta, \theta') = \ln \pi(x, s^*(\theta), \phi^*(\theta)|\theta') \tag{16}$$

$$s^*(\theta), \phi^*(\theta) = \operatorname*{argmax}_{s,\phi} \pi(s, \phi|x, \theta) \tag{17}$$

Given an initial parameter vector θ, therefore, it is possible to find a new parameter vector θ' with higher likelihood by computing its maximum-likelihood senone sequence and phone sequence $s^*(\theta), \phi^*(\theta)$, and by maximizing θ' with respect to $s^*(\theta)$ and $\phi^*(\theta)$. Maximizing $R(\theta, \theta')$ rather than $Q(\theta, \theta')$ is useful for probabilistic transcription because it reduces the importance of poor phonetic transcripts.

C. Using a Language Model During Training

During segmental K-means, it is advantageous to incorporate as much information as possible about the utterance language. Define G to be an FST representing the modeled phone bigram probability $\pi(\phi^\ell|\theta) = \prod_{m=1}^{M} \pi(\phi^\ell_m|\phi^\ell_{m-1}, \theta)$. Training results can be improved by using $H \circ C \circ PT \circ G$ to compute segmental K-means.

By assumption, phone bigram information is not available from speech: we assume that there is no transcribed speech in the target language. A reasonable proxy, however, can be constructed from text. Fig. 5 shows text data downloaded from Wikipedia in Swahili, and a segment of a character-based G2P for the Swahili language. By passing the former through the latter, it is possible to generate synthetic phone sequences in the target language.

Composing $PT \circ G$ is complicated by the presence of null transitions in the PT. A null transition in the PT matches a non-event in the language model, for which normal FST notation has no representation. In

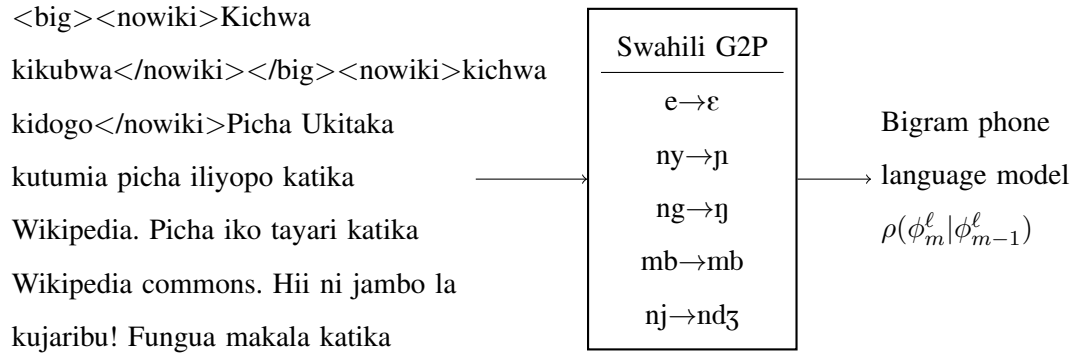
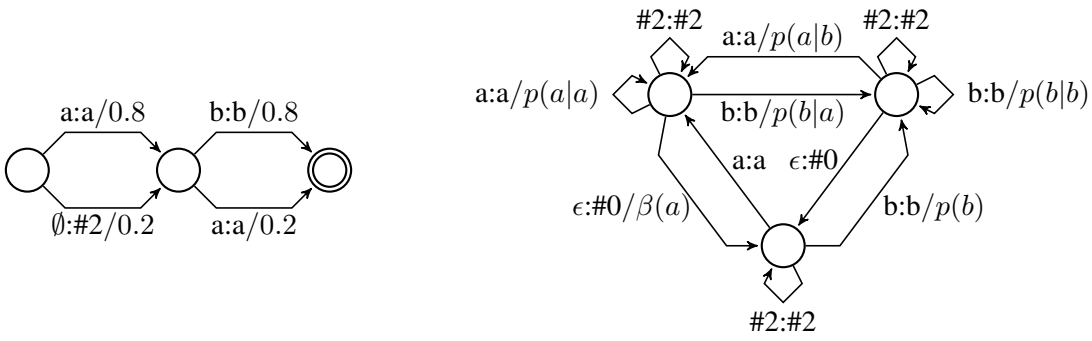


Fig. 5. Bigram phone language model is trained using Wikipedia text (left) converted into phone strings using a character-based G2P (center).



(a) Probabilistic Transcript, PT (b) Language Model, G

Fig. 6. Deletion edges in the probabilistic transcript (edges with the special null-phone symbol, $\emptyset$), required special handling in order to use information from a phone language model. As shown in (a), a new type of null symbol, "#2", was invented to represent the output for every PT edge with an $\emptyset$ input. Such edges were only allowed to match with state self-loops, newly added to the language model (b) in order to consume such non-events in the transcript. a,b: regular phone symbols, ϵ: null-string, $p(b|a)$: bigram probability, $\beta(a)$: language model backoff.

order to compose the PT with the language model, therefore, it is necessary to introduce a special type of "non-event" symbol, here denoted "#2", into the language model (Fig. 6). A language model "non-event" is a transition that leaves any state, and returns to the same state (a self-loop). Such self-loops, labeled with the special symbol "#2" on both input and output language, are added to every state in G (Fig. 6 (b)). The probabilistic transcript, then, is augmented with the special symbol "#2" as the output-language symbol for every null-input edge (input symbol is $\phi_m^\ell = \emptyset$).

D. *Maximum* A Posteriori *Adaptation*

PT adaptation starts from a cross-lingual ASR, and adapts its parameters to PTs in the target language. The Bayesian framework for maximum *a posteriori* (MAP) estimation has been widely applied to GMM and HMM parameter estimation problems such as speaker adaptation [12]. Formally, for an unseen target language, denote its acoustic observations $x = (x_1^1, \ldots, x_T^L)$, and its acoustic model parameter set as θ, then the MAP parameters are defined as:

$$\theta_{\mathrm{MAP}} = \operatorname*{argmax}_{\theta} \pi(\theta|x) = \operatorname*{argmax}_{\theta} \pi(x|\theta)\pi(\theta) \tag{18}$$

where $\pi(\theta)$ is the product of conjugate prior distributions, centered at the parameters of a cross-lingual baseline ASR. In a GMM-HMM, the acoustic model is computed by choosing a Gaussian component, G_t^ℓ, whose mixture weight is $c_{jk} = \pi_{G_t^\ell|S_t^\ell}(k|j)$, and whose mean vector and covariance matrix are μ_{jk} and Σ_{jk}. Maximum likelihood trains these parameters by computing $\gamma_t^\ell(j,k) = \pi_{S_t^\ell,G_t^\ell}(j,k|x^\ell,\theta)$, then accumulating weighted average acoustic frames with weights given by $\gamma_t^\ell(j,k)$. Segmental K-means quantizes $\pi_{S_t^\ell}(j|x^\ell,\theta) \rightarrow \{0,1\}$ using forced alignment, then proceeds identically. MAP adaptation assigns, to each parameter, a conjugate prior $\pi(\theta)$ with mode equal to $\bar{\theta}$ (the parameters of the cross-lingual baseline), and with a confidence hyperparameter τ_θ, resulting in re-estimation formulae that are linearly interpolated between the baseline parameters $\bar{\theta}$ and the statistics of the adaptation data, for example:

$$c'_{jk} = \frac{\tau_c \bar{c}_{jk} + \sum_{\ell,t} \gamma_t^\ell(j,k)}{\sum_n \left(\tau_c \bar{c}_{jn} + \sum_{\ell,t} \gamma_t^\ell(j,n)\right)} \tag{19}$$

E. *Neural Networks*

The NN acoustic model is $\pi_{X_t^\ell|S_t^\ell}(v|j,\theta) \propto y_t^\ell(j)$,

$$y_t^\ell(j) = \frac{1}{c_j} \frac{\exp\left(w_j^T h_t(v, w_{vh})\right)}{\sum_k \exp\left(w_k^T h_t(v, w_{vh})\right)} \tag{20}$$

whose parameters $\theta = \{c_j, w_j, w_{vh}\}$ include the senone priors c_j, the softmax weight vectors w_j, and the parameters defining the hidden nodes $h_t(v, w_{vh})$. NNs are trained by using a GMM-HMM to compute an initial senone posterior, $\pi_{S_t^\ell}(j|x^\ell,\theta)$, then minimizing the cross-entropy between the estimated senone posterior and the neural network output $y_t^\ell(j)$, using gradient descent in the direction

$$-\nabla_\theta H(S^\ell \| Y^\ell) = \sum_{t=1}^{T} \sum_j \frac{\pi_{S_t^\ell}(j|x^\ell,\theta)}{y_t^\ell(j)} \nabla_\theta y_t^\ell(j) \tag{21}$$

NN training with deterministic transcripts is improved by quantizing $\pi_{S_t^\ell}(j|x^\ell,\theta) \rightarrow \{0,1\}$ using forced alignment [7]. Preliminary experiments showed that forced alignment also improves the accuracy of NNs

trained from probabilistic transcripts: the best path through the PT, and the best alignment of the resulting senones to the waveform, were both computed using forced alignment. The resulting best senone string was used to train a NN using Eq. (21).

V. Experimental Methods

ASR was trained in four target languages, each using no native transcripts. Unspoken texts and untranscribed audio were acquired in seven languages (Sec. V-A). Texts from mismatched crowdsourcing were decoded using a multilingual misperception G2P (Sec. V-B), or using a language-specific misperception G2P estimated using EEG (Sec. V-C). Baseline cross-lingual systems were trained using native transcripts from six different languages not including the target language (Section V-D). Finally, parameters of the acoustic model were adapted using PTs in the target language, derived from either self-training or from mismatched transcripts (Sec. V-E).

A. Data

Speech data were extracted from publicly available podcasts [41] hosted in 68 different languages. In order to generate test corpora (in which it is possible to measure phone error rate), advertisements were posted at the University of Illinois seeking native speakers willing to transcribe speech in any of these 68 languages. Of the ten transcribers who responded, six people were each able to complete one hour of speech transcription (the other four dropped out). One additional language was transcribed by workers recruited at I^2R in Singapore, yielding a total of seven languages with native transcripts suitable for testing an ASR: Arabic (arb), Cantonese (yue), Dutch (nld), Hungarian (hun), Mandarin (cmn), Swahili (swh) and Urdu (urd).

The podcasts contain utterances interspersed with segments of music and English. A GMM-based language identification system was developed in order to isolate regions that correspond mostly to the target language, which were then split into 5-second segments to enable easy labeling by the native transcribers. Native transcribers were asked to omit any 5-second clips that contained significant music, noise, English, or speech from multiple speakers. Resulting transcripts covered 45 minutes of speech in Urdu and 1 hour of speech in the remaining six languages. The orthographic transcripts for these clips were then converted into phonemic transcripts using language-specific dictionaries and G2P mappings (these resources are detailed in Section V-D). For each language, we chose a random 40/10/10 minutes split into training, development and evaluation sets.

B. Mismatched Crowdsourcing

Mismatched transcripts were collected from crowd workers (Turkers) on Amazon Mechanical Turk. Each 5-sec speech segment was further split into 4 non-overlapping segments to make the non-native listening task easier. The crowdsourcing task was set up as described in [23]; briefly, the segments were played to Turkers, who transcribed what they heard (typically in the form of nonsense syllables) using English orthography. Each segment was transcribed by 10 distinct Turkers. More than 2500 Turkers participated in these tasks, with roughly 30% of them claiming to know only English (Spanish, French, German, Japanese, Chinese were some of the other languages listed by the Turkers).

C. EEG Recording and Analysis

To compute distinctive feature weights for the misperception transducer shown in Eqs. (4) and (5), cortical activity in response to non-native phones was recorded by an EEG. Signals were acquired using a BrainVision actiCHamp system with 64 channels and 1000 Hz sampling frequency. All procedures were approved by the University of Washington Institutional Review Board.

Auditory stimuli were consonant-vowel (CV) syllables representing consonants of three languages: English, Dutch and Hindi. The inclusion of only two non-English languages was dictated by the relatively high number of repetitions needed for good signal-to-noise ratio from averaged EEG recordings. The choice of Dutch and Hindi was made based on language phonological similarity, defined as the number of many-to-one mappings (N_{M2O}) between the English phoneme inventory and the non-English phoneme inventory. Many-to-one mappings are expected to pose a problem for the non-native transcription task being modeled by the misperception transducer, so to test the contribution of EEG we chose languages that differed greatly in this property. Using distinctive feature representations of the phonemes in each inventory from the PHOIBLE database [32], a many-to-one mapping was defined by finding, for each non-English phoneme ϕ, the English phoneme $\psi^*(\phi)$ to which it is most similar. The number of many-to-one collisions is then defined as

$$N_{M2O} = \frac{1}{|\Omega_\Psi|} \sum_{\phi_1 \neq \phi_2} [\psi^*(\phi_1) = \psi^*(\phi_2)] \tag{22}$$

where $|\Omega_\Psi|$ is the size of the English phoneme inventory, and $[\cdot]$ is the unit indicator function. The frequency of many-to-one mappings is listed in Table I for several languages. Hindi was chosen for having a large number of many-to-one mappings with English, while Dutch has relatively few. Note that, although Hindi podcasts were not included in the training data described in Section V-A, colloquial spoken Hindi and Urdu are extremely similar phonologically [24], and considering that the auditory

Language	N_{M2O}	Language	N_{M2O}	Language	N_{M2O}
spa	0.862	yue	1.280	cmn	1.531
por	1.152	jpn	1.333	amh	1.844
nld	1.182	vie	1.393	hun	1.857
deu	1.258	kor	1.429	hin	2.848

TABLE I

FREQUENCY OF MANY-TO-ONE MAPPINGS N_{M2O} BETWEEN OTHER LANGUAGES' PHONEME INVENTORIES AND THE INVENTORY OF ENGLISH. LANGUAGES ARE REPRESENTED BY THEIR ISO 639-3 CODES.

	Consonants used in the EEG experiment									
eng	p	t	k	tʃ	v	ð	z	m	n	
nld	p	t	ɣ		v		z	m	n	
hin	p b	t̪ d̪ ʈ ɖ	k g		ʋ			m	n̪	ɳ
eng	p^h	t^h	k^h	$tʃ^h$	f	θ	ʃ	l	ɹ	
nld	p^h	t^h	k^h	$tʃ^h$	f		ʃ	l	ʁ	j
hin	$b^{ɦ}$	$t̪^h$ ʈ^h $d̪^{ɦ}$ ɖ^{ɦ}	k^h $g^{ɦ}$							

TABLE II

CONSONANT PHONES USED IN THE EEG EXPERIMENT REPRESENTED USING IPA. VERTICAL ALIGNMENT OF CELLS SUGGESTS MANY-TO-ONE MAPPINGS EXPECTED BASED ON DISTINCTIVE FEATURE VALUES.

stimuli for the EEG portion of this experiment are simple CV syllables, it is reasonable to consider Hindi and Urdu as equivalent for the purpose of computing feature weights for the misperception transducer.

To construct the auditory stimuli, two vowels and several consonants were selected from the phoneme inventory of each language (18 consonants for English, 17 for Dutch, and 19 for Hindi). Consonants were chosen to emphasize differences in the many-to-one relationships between English-Dutch and English-Hindi, while maintaining roughly equal numbers of consonants for each language. The consonants chosen for each language are given in Table II; the vowels chosen were the same for all three languages (/a/ and /e/).

Two native speakers of each language (one male and one female) were recorded (44100 Hz sampling frequency, 16 bit depth) speaking multiple repetitions of the set of CV syllables for their language. Three tokens of each unique syllable were excised from the raw recordings, downsampled to 24414 Hz, and RMS normalized. Recorded syllables had an average duration of 400 ms, and were presented via headphones to one monolingual American English listener. The stimuli were presented in 9 blocks of

15 minutes per block, for a total of 135 minutes. Syllables were presented in random order with an inter-stimulus interval of 350 ms. Twenty-one repetitions of each syllable were presented, for a grand total of 9072 syllable presentations.

EEG recordings were divided into 500 ms epochs. The epoched data were coded with a subset of distinctive features that minimally defined the phoneme contrasts of the English consonants. Where more than one choice of features was sufficient to define those contrasts, preference was given to features that reflect differences in temporal as opposed to spectral features of the consonants, due to the high fidelity of EEG at reflecting temporal envelope properties of speech [9]. The final set of features chosen was: continuant, sonorant, delayed release, voicing, aspiration, labial, coronal, and dorsal.

D. Cross-Lingual Baselines

The goal of building a cross-lingual system is two-fold. One is to define a baseline for generalizing to an unseen language without any labeled audio corpus. The other is have the baseline serve as a starting point for adaptation.

The dataset consists of 40 minutes of labeled audio for training, 10 minutes for development, and 10 minutes for testing for each language. English words in each transcript are identified and converted to phones with an English G2P trained using CMUdict [26], then other words are converted into phonetic transcripts using language-dependent dictionaries and G2Ps. The Arabic dictionary is from the Qatari Arabic Corpus [11], the Dutch dictionary is from CELEX v2 [1], the Hungarian dictionary was provided by BUT [13], the Cantonese dictionary is from I^2R, the Mandarin dictionary is from CALLHOME [6], and the Urdu and Swahili G2Ps were compiled from character-based descriptions of the orthographic systems in those two languages.

Each HMM was trained with data from six languages, tuned (stream weight and insertion penalty) on the development set of the seventh language, and tested on the evaluation set of the seventh language. The lexicon of the target language was not used during testing, but two types of language-dependent specialization were allowed. In the first type of specialization, the universal phone set was restricted at test time to output only phones in the target language. In the second type of specialization, a target-language phone bigram language model was trained using phone sequences converted from Wikipedia texts. As an oracle experiment, we also train language dependent HMMs for each individual language with 40 minutes of labeled audio.

Method	nld	cmn	urd	arb	hun
Universal set	87.4	88.86	97.95	79.04	92.87
Target set	78.12	87.4	87.81	66.39	84.78
Phone bigram	68.61	70.88	64.67	65.29	63.98

TABLE III

LABEL PHONE ERROR RATE (LPER) OF PROBABILISTIC TRANSCRIPTS FOR UNIVERSAL PHONE SET, TARGET-LANGUAGE PHONE SET, TEXT-BASED PHONE BIGRAM.

E. MAP Adaptation to Probabilistic Transcripts

The baseline and the adapted models were implemented using Kaldi [34]. In order to efficiently carry out the required operations on the cascade $H \circ C \circ PT \circ G$, PT was defined as $\mathrm{proj}_{\mathrm{input}}(\widehat{PT})$, where $\widehat{PT}$ is a wFST mapping phone sequences to English letter sequences (Eq. 2), and $\mathrm{proj}_{\mathrm{input}}$ refers to projecting onto the input labels. For the purposes of computational efficiency, the cascade for $\widehat{PT}$ includes an additional wFST restricting the number of consecutive deletions of phones and insertions of letters (to a maximum of 3). Two additional disambiguation symbols [31] were used to determinize these insertions and deletions in $\widehat{PT}$. MAP adaptation for the acoustic model was carried out for a number of iterations (12 for yue & cmn, 14 for hun & swh, with a re-alignment stage in iteration 10).

VI. EXPERIMENTAL RESULTS

This section reports two types of results. First, subsections VI-A and VI-B report improvements in the quality of probabilistic transcripts using information acquired from text-based phone language models and EEG signals, respectively. Second, subsections VI-C and VI-D report the accuracy of cross-lingual ASR and PT-adapted ASR, respectively.

A. Mismatched Crowdsourcing

The quality of a probabilistic transcript derived from mismatched crowdsourcing is significantly improved by using a phone language model during the decoding process ($\rho(\phi)$ in Eq. (2)). Phone language models for each target language were computed from Wikipedia texts using the methods described in Sec. IV-C. Label phone error rate (LPER) of the 1-best path through the resulting PTs are shown in Table III, computed with reference to a native transcript in each language. As shown, the use of a phone language model, derived from Wikipedia text, reduces LPER by about 10% absolute, in each language.

LPER of the 1-best path does not accurately reflect the extent of information in the PTs that can be leveraged during ASR adaptation. Consider, for example, the four Urdu phones [p,p$^{\mathrm{h}}$,b,b$^{\mathrm{fi}}$]. An attentive

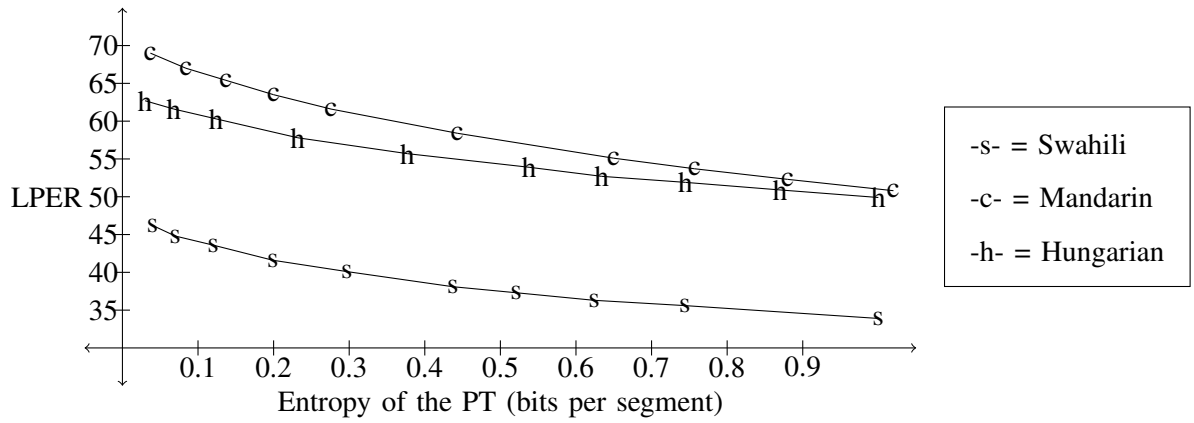


Fig. 7. LPER plotted against entropy rate estimates of phone sequences in three different languages.

English-speaking transcriber must choose between the two letters <p,b> in order to represent any of these four phones. The misperception G2P therefore maps the letters <p,b> into a distribution over the phones [p,p$^{\text{h}}$,b,b$^{\text{fi}}$]. There is no reason to expect that the maximizer of $\rho(\phi|\lambda)$ is correct, but there is good reason to expect the correct answer to be a member of a short N-best list ($N \leq 4$ phones/grapheme). A fuller picture is therefore obtained by considering a collection of sequences that are almost equally probable according to our model. Figure 7 shows the trend of LPER (for three languages) obtained by using collections ϕ of increasing size, plotted against an entropy estimate of $\rho(\phi)$, e.g., 1 bit of entropy allows two equally probable choices for each phone in ϕ. LPER rates drop significantly across all languages within 1 bit of entropy per phone, illustrating the extent of information captured by the PTs.

B. Misperception Transducer Trained Using EEG

Epoched and feature-coded EEG data *for the English syllables only* were used to train a support vector machine classifier for each distinctive feature. The classifiers were then used (without re-training) to classify the EEG responses to the Dutch and Hindi syllables. Fig. 8 shows equal error rates of these classifiers when applied to the three languages.

Eq. (4) defines a log-linear model of $\rho(\psi|\phi)$, the probability that a non-English phoneme ϕ will be perceived as English phoneme ψ. Denote by $\rho_U(\psi|\phi)$ the model of Eq. (4) with uniform binary weights for all distinctive features. Denote by $\rho_{EEG}(\psi|\phi)$ the same model, but with weights w_k derived from EEG measurements (Eq. (5)). Fig. 9 shows these two confusion matrices: $\rho_U(\psi|\phi)$ on the left, $\rho_{EEG}(\psi|\phi)$ on the right. The entropy of the binary weighting, $\rho_U(\psi|\phi)$, is too low: when a Dutch phoneme ϕ has a nearest-neighbor $\psi^*(\phi)$ in English, then few other phonemes are considered to be

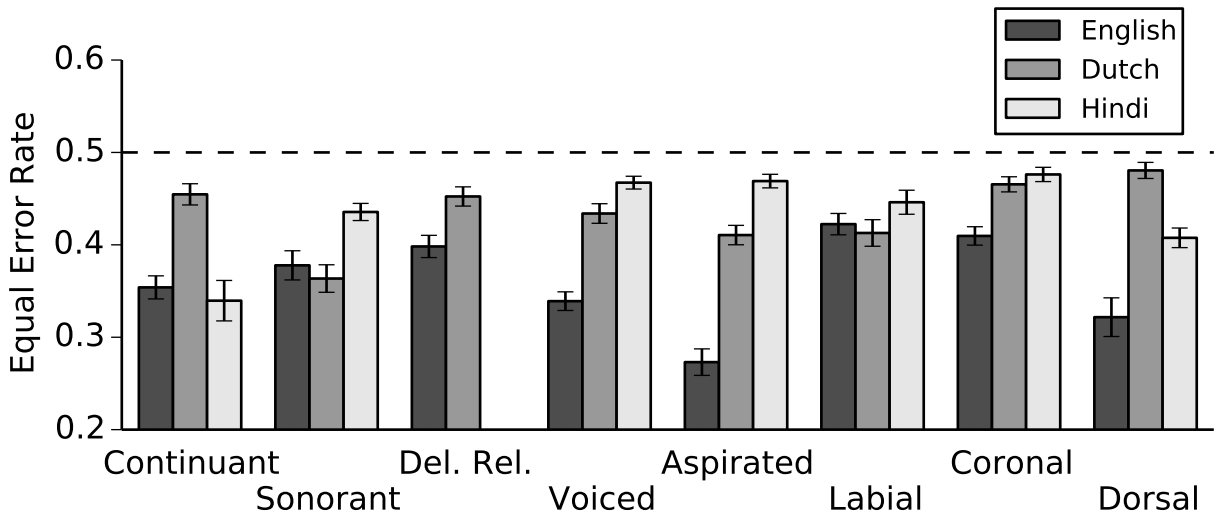


Fig. 8. Classifiers were trained to observe EEG signals, and to classify the distinctive features of the phone being heard. Equal error rates are shown for English (the language used in training; train and test data did not overlap), Dutch, and Hindi. Dashed line shows chance=50%.

possible confusions. $\rho_{EEG}(\psi|\phi)$ has a very different problem: since distinctive feature classifiers have been trained for only a small set of distinctive features, there are large groups of phonemes whose confusion probabilities can not be distinguished (giving the figure its block-matrix structure). The faults of both models can be ameliorated by averaging them in some way, e.g., by computing the linear interpolation $\rho_I(\psi|\phi) = \alpha\rho_U(\psi|\phi) + (1-\alpha)\rho_{EEG}(\psi|\phi)$ for some constant $0 \leq \alpha \leq 1$.

In order to evaluate the effectiveness of the EEG-induced misperception transducer we looked at the LPER of mismatched crowdsourcing for Dutch when performed using 1) a multilingual misperception model $\rho(\lambda|\phi)$, 2) feature-based misperception transducer computed using binary weighting, $\rho_U(\psi|\phi)$, or 3) EEG-induced transducer combined with the feature-based transducer, $\rho_I(\psi|\phi)$. To combine the two transducers, the value of the parameter α was optimized on a separate development data set. LPER of the multilingual model was 70.43%, of the feature-based model, 69.44%, and of the EEG-interpolated model, 68.61%.

C. Cross-Lingual Baseline

The first four columns of Table IV compare a monolingual ASR with phone language model based on monolingual transcripts, a cross-lingual ASR using universal phone set and phone language model, and a cross-lingual ASR using a phone language model based on language-dependent Wikipedia texts.

The monolingual ASR is trained using only 40 minutes of audio and transcript data per language, but

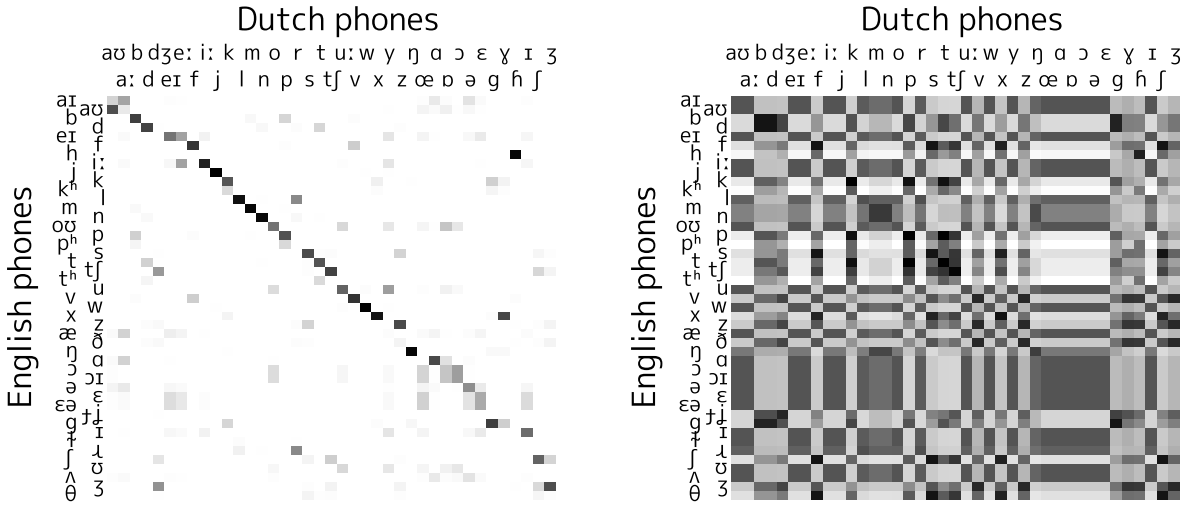


Fig. 9. Phone confusion probabilities between English and Dutch phones using models in which the negative log probability is proportional to unweighted or weighted distance between the corresponding distinctive feature vectors. Left: unweighted. Right: feature weights equal negative log confusion probability of EEG signal classifiers.

performs reasonably well (31.58% average PER, NN-HMM). The cross-lingual ASRs, however, perform poorly. Using a language-specific phonotactic language model gives significant improvement over the language-independent phonotactic model, but significantly underperforms a system that has seen the test language during training. This is true even if the system has seen closely related languages during training: the Cantonese cross-lingual system has seen Mandarin during training, and the Mandarin system has seen Cantonese during training, but neither system is able to generalize well from its six training languages to its test language.

D. ASR Trained Using Probabilistic Transcripts

Table IV presents phone error rates (PERs) on the evaluation (and development) sets for four different languages. The column titled CL lists cross-lingual baseline error rates. The column labeled ST lists the PERs of self-trained ASR systems. The column headed PT-ADAPT in Table IV lists PERs from CL ASR systems that have been adapted to PTs in the target language.

Self-training was only performed using NN systems; no self-training of GMMs was performed, because previous studies [15] reported it to be less effective. Differences between the evaluation set PERs of ST and CL systems were tested for statistical significance using the MAPSSWE test of the `sc_stats` tool [33]. There are 20 independent statistical comparisons in Table IV; the study-corrected significance

Acoustic Model	Monolingual	Cross-Lingual (CL)		Self-training (ST)	CL + PT adaptation (PT-ADAPT)
Language Model	Transcript	CL	Text	Text	Text
GMM-HMM					
yue	32.77 (34.61)	79.64 (79.83)	68.40 (68.35)		**57.20*** (56.57)**
hun	39.58 (39.77)	77.13 (77.85)	68.62 (66.90)		**56.98*** (57.26)**
cmn	32.21 (26.92)	83.28 (82.12)	71.30 (68.66)		**58.21*** (57.85)**
swh	35.33 (46.51)	82.99 (81.86)	63.04 (64.73)		**44.31*** (48.88)**
NN-HMM					
yue	27.67 (28.88)	78.62 (77.58)	66.59 (65.41)	63.79 (n.s.) (62.46)	**53.64*** (53.80)**
hun	35.87 (36.58)	75.98 (76.44)	66.43 (67.18)	63.53 (n.s.) (63.50)	**56.70*** (58.45)**
cmn	27.80 (23.96)	81.86 (80.47)	65.77 (64.80)	64.90* (64.00)	**54.07*** (53.13)**
swh	34.98 (41.47)	82.30 (81.18)	65.30 (65.11)	58.76** (59.81)	**44.73*** (48.60)**

TABLE IV

PERS ON THE EVALUATION AND DEVELOPMENT SETS (DEVELOPMENT IN PARENTHESES) BEFORE AND AFTER ADAPTATION WITH PTS. MAPSSWE SIGNIFICANCE TESTING WITH RESPECT TO CL ACOUSTIC MODEL WITH TEXT-BASED LANGUAGE MODEL: * MEANS $p \leq 0.003$, ** MEANS $p < 0.001$, (N.S.) MEANS NOT SIGNIFICANT. *** DENOTES A SCORE LOWER THAN BOTH CL AND ST BASELINES AT $p < 0.001$.

level of $0.05/20 = 0.0025$ was rounded up to 0.003 because `sc_stats` only provides three significant figures. The Mandarin ST system was judged significantly better than CL at a level of $p = 0.003$ (denoted *), and the Swahili system at a level of $p < 0.001$ (denoted **); the Cantonese and Hungarian ST systems were judged to be not significantly better than CL.

The relative reductions in PER of the PT-ADAPT system compared to both CL and ST baselines were tested for statistical significance using the MAPSSWE test of the `sc_stats` tool. All differences were found to be statistically significant at $p < 0.001$ (denoted ***). This suggests that adaptation with PTs is providing more information than that obtained by model self-training alone.

PER improvements for Swahili are larger than for the other three languages. We conjecture this may be due to the relatively good mapping between Swahili's phone inventory and that of English. For example: all Swahili vowel qualities are also found in English, and the Swahili phonemes that would be unfamiliar to an English speaker (prenasalized stops, palatal consonants) have representations in English orthography that are fairly natural ("mb", "nd", etc. for prenasalized stops; "tya", "chya", "nya", etc. for palatals). In contrast: Mandarin, Cantonese, and Hungarian each have at least two vowel qualities not found in English; Mandarin and Cantonese have many diphthongs not found in English; and some of the consonant phonemes (e.g., Mandarin retroflexes) do not have representations in English orthography that are obvious

or straightforward.

It is also useful to compare the performance of GMM-HMM and NN-HMM systems. In the CL setting, an ASR trained using six languages is then applied to an unseen seventh language, without adaptation; in this setting, the NN consistently outperforms the GMM. In the PT-ADAPT setting, GMMs and NNs are adapted using PTs in the target language. PT adaptation improves the performance of both types of ASR, but the adapted NN does not consistently outperform the GMM across all tested languages.

VII. DISCUSSION

Models of human neural processing systems have often been used to inspire improvements in machine-learning systems (for a catalog of such approaches and a warning, see [4]). These systems are often called neuromorphic, because the system is engineered to mimic the behavior of human neural systems. In contrast to that approach, our incorporation of EEG signals into ASR resonates with the Human Aided Computing approach used in computer vision [39], [47]. Together with our EEG work presented here, this class of approach represents a less explored direction for design of machine learning systems, whereby recorded neural data (rather than neuro-inspired models) are used as a source of prior information to improve system performance. Therefore, our work here suggests that, by thinking about the kinds of prior information required by a machine learning system, engineers and neuroscientists can work together to design specific neuroscience experiments that leverage human abilities and provide information that can be directly integrated into the system to solve an engineering problem.

NN-HMM outperforms the GMM-HMM in all baseline conditions, but not always when adapted using PTs. Preliminary analysis suggests that the NN is more adversely affected than the GMM by label noise in the PTs. A NN is trained to match the senone posterior probabilities $\pi(s_t^\ell|x^\ell, \phi^\ell, \theta)$ computed by a first-pass GMM-HMM. Many papers have demonstrated that entropy in the senone posteriors is detrimental to NN training, and that the senone posteriors should therefore be quantized ($\pi(s_t^\ell) \rightarrow \{0, 1\}$) prior to NN training. In PT adaptation, however, entropy is unavoidable, and quantizing the forced alignment doesn't necessarily help. Table III showed that the 1-best path through the PT is only correct for 29-49% of all phones, depending on language. There is good reason for this: the transcribers don't speak the target language, so they find some of its phone pairs to be perceptually indistinguishable. Future work will seek methods that can improve the robustness of NN training in the face of label noise.

This paper has tentatively defined an "under-resourced language" to be one that lacks transcribed speech data. Other authors have proposed that if a language lacks transcribed speech, ASR can be initialized in that language by adapting a cross-lingual baseline. Other authors have proposed, and Table IV confirms, that significant error reductions can be achieved using self-training: by automatically labeling speech in

the target language, and adding the self-labeled data to the training set. Table IV shows that further error rate reductions can be achieved using mismatched crowdsourcing: by asking non-speakers of the target language to write down what they hear, and by interpreting their nonsense orthography as information about the phonetic content of the utterances. The PER of mismatched crowdsourcing (Table III) is almost as high as the PER of cross-language ASR (Table IV), but the information provided by mismatched crowdsourcing is superior to that provided by self-training in the sense that it trains a better ASR.

VIII. Conclusions

When a language lacks transcribed speech, other types of information about the speech signal may be used to train ASR. This paper proposes compiling the available information into a probabilistic transcript: a pmf over possible phone transcripts of each waveform. Three sources of information are discussed: self-training, mismatched crowdsourcing, and EEG distribution coding. Experiments demonstrate that self-training outperforms cross-lingual ASR in two of the four test languages (Mandarin and Swahili). Adaptation using mismatched crowdsourcing outperforms both cross-lingual ASR and self-training in all four of the test languages. Auxiliary information from EEG is used, together with text-based phone language models, to improve the decoding of transcripts from mismatched crowdsourcing.

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