



# How much does grouping talkers help with speech perception?

## Introduction

Variability is one of the defining features of speech. There are two broad traditions in the study of speech, with very different approaches to the role of *variability* in speech. On the one hand, for the cognitive/psycholinguistic tradition, variability is one of the central *problems* of speech perception, a challenge that listeners must cope with. In this view, variability is such a severe problem that it is traditionally referred to only indirectly, as the “lack of invariance” (Liberman et al. 1967). The sociolinguistic tradition, on the other hand, views variability as a rich source of social information. The particular variety of language that you speak says a lot about who you are as a person, and sociolinguistics takes this sort of variation as one of its primary objects of study (Labov 1972; Eckert 1989).



These two approaches have recently begun to converge in how they approach variability. In particular, psycholinguistic theories of speech perception have started to investigate the consequences of variability for comprehension. In part this realization comes from computational-level analyses of speech perception (Clayards et al. 2008; Feldman, Griffiths, and Morgan 2009; Feldman et al. 2013; Norris and McQueen 2008; Kleinschmidt and Jaeger 2015). These approaches start from the hypothesis that the speech perception system is organized in order to be good at speech perception in the world that it has to operate in. In the spirit of ideal observer approaches to other domains (like visual perception, Marr 1982; or memory, Anderson 1990; Anderson 1991) these approaches focus on spelling out how the nature of the task, the available information, and the structure of the world constrain, in principle, how well a listener can do.

Applied to speech perception, this approach offers two important insights. First, it suggests that speech perception can be thought of as a process of *inference under uncertainty* (Clayards et al. 2008; Norris and McQueen 2008): each linguistic unit is realized—even by a single talker—as a *distribution* of acoustic cues (cf. Lisker and Abramson 1964; Peterson and Barney 1952; Hillenbrand et al. 1995; Allen, Miller, and DeSteno 2003; Newman, Clouse, and Burnham 2001). This places a fundamental constraint on speech perception: the best a listener can do is to *infer* how likely each possible linguistic unit is as an explanation of the cues they observe, based on their knowledge of these cue distributions.

Second, this approach provides a new perspective on talker variability. One consequence of talker variability is that the distribution of cues for each linguistic unit *changes* from one situation to the next, depending on who’s talking (Clopper, Pisoni, and Jong 2005; Newman, Clouse, and Burnham 2001; Allen, Miller, and DeSteno 2003; Johnson 2005; Foulkes and Hay 2015). Moreover, these differences cannot be entirely reduced to constant effects of physiological differences (like vocal tract size, Johnson 2005; for review see Weatherholtz and Jaeger 2016). In this perspective, effective speech perception depends on good knowledge of the underlying cue distributions. Because these distributions change across situations, listeners must *also* constantly be inferring the current talker’s linguistic generative model (the probabilistic distributions of cues they produce for each underlying linguistic structure). This is captured by the ideal adapter framework (Kleinschmidt and Jaeger 2015).

**This second insight leads to the following prediction:** an ideal adapter will take advantage of any additional structure in the world that is informative about how cue distributions vary from one situation to the next. This structure may be as simple as the fact that individual talkers tend to be consistent in the cue distributions they produce (Heald and Nusbaum 2015; see also Weatherholtz et al. 2016), meaning that prior experience with a familiar talker is informative about the cue distributions they will produce in the future. But structure can occur at other levels, too, and here is one place that psycholinguistic theories begin to parallel sociolinguistics. To the extent that variables like gender, class, regional origin, etc. are sociolinguistically relevant, they are reliably informative about how linguistic variables are realized, and hence helpful for speech perception.

This means that a listener can potentially learn a lot about a talker’s cue distributions just by knowing *who* a talker is. Conversely, listeners can learn a lot about who a talker is based on the distributions of cues that they produce. This bi-directional relation between phonetic cues and social identity has long been recognized in sociolinguistics. This relationship *also* follows straightforwardly from the ideal adapter framework. However, the extent to which these two types of inferences—socio-indexically-conditioned linguistic inference and

linguistically-conditioned inference about social identity—are feasible *in practice* depends on exactly how much a particular socio-indexical variable—a particular sense of *who* a talker is—actually influences the cue distributions that talkers produce.

One advantage of the ideal adapter framework over previous approaches to these issues is that it provides a set of computational and theoretical tools to quantify this relationship. The central question we address in this paper is twofold: 1) how much can listeners actually gain by considering socio-indexical variables for speech perception (both in absolute terms and relative to other grouping variables), and 2) **how accurately could listeners infer socio-indexical grouping variables** for a talker on the basis of their cue distributions.



## Our goals

At a conceptual level, the goal of this paper is to show that the idea of *inference* provides a bridge between sociolinguistic and psycholinguistic perspectives on variation in speech. The ideal adapter framework treats both linguistic and socio-indexical judgements as inference, jointly informed by a listener’s knowledge of cue distributions. In addition to this conceptual unification, the theoretical tools of this framework offer a common computational currency for developing models of linguistic and socio-indexical inference, and, critically, for grounding the parameters of those models in actual data. This common currency is the *distribution* of cues *conditioned* on linguistic and socio-indexical variables. These distributions can be measured, given the appropriate production data.

This brings us to the more concrete, immediate goal of this paper, which is to quantify the relationship between some prominent socio-indexical variables, linguistic variables, and acoustic-phonetic cue distributions. Most (but not all, e.g., Clopper, Pisoni, and Jong 2005; McMurray and Jongman 2011) of the work on this relationship has been descriptive, aimed at establishing that differences between particular groups of talkers *exist* in the first place, and that listeners are sensitive to these differences at all. But the mere existence of differences does not establish exactly how *informative* or *useful* such grouping variables are for speech perception. As we discuss in more detail below, we focus on three interrelated ways of quantifying this relationship:

1. How *informative* are socio-indexical variables about the distribution of different acoustic-phonetic cues? This can be quantified by the KL divergence of the distribution of cues produced by a particular group and the distribution of cues produced by all talkers.
2. How *useful* is socio-indexical grouping for correct speech recognition? We quantify this by the *probability of correct recognition* of phonetic categories, using an ideal listener model that knows that group-specific cue distributions of each phonetic category.
3. **How well can you *infer* socio-indexical variables based on acoustic-phonetic cue distributions alone? Like the usefulness of a grouping variable, this too can be quantified as probability of correct recognition, but recognition of the *group*, by the same kind of ideal listener model that knows the distribution of cues that each group produces.**

We apply these measures at different levels of socio-indexical grouping, and for two different sets of phonetic cues/contrasts (vowels, cued by first and second formant frequencies, and word-initial stop voicing, cued by voice onset time, VOT). To anticipate our results, we find that the informativity and utility of socio-indexical variables differs substantially depending on the contrast, categories, and particular way of representing input.

The socio-indexical variables that we focus on are variables that are generally *stable* over time for a single talker, like sex or regional origin. This is largely a matter of convenience: our analysis depends on having sufficient data to estimate cue distributions for multiple talkers, within groups defined by socio-indexical variables. Sociolinguistics increasingly recognizes that the meanings of socio-indexical variables are dynamically constructed  not necessarily static within a single individual (either producer or perceiver; Foulkes and Hay 2015; n 2014). The same computational techniques can—in principle—be applied to dynamic variables, ~~but they present unique and interesting challenges that are beyond the scope of the current paper.~~

Finally, beyond connecting sociolinguistic and psycholinguistic perspectives on variability in speech perception, quantifying the relationship between socio-indexical variables, linguistic variables, and cue distributions is

critical for refining the qualitative predictions of the ideal adapter framework (Kleinschmidt and Jaeger 2015). In the ideal adapter framework, whether or not a listener is predicted to track cue distributions conditioned on a particular grouping variable (sex or dialect) critically depends on the informativity and utility of that grouping for speech perception.

Next, we briefly review the relevant literature on the relationship between the socio-indexical and linguistic variables we consider. Then we describe the datasets we will analyze, the techniques we use, our findings, and finally the conclusions we can draw.

## Background

What do we already know about the relationship between speech perception and socio-linguistic variables?<sup>1</sup>

First, we know that the *amount* and *structure* of talker variability differs between cues and phonetic categories. Vowels and fricatives have a lot of talker variability, which is at least in part conditioned on sex (Peterson and Barney 1952; Hillenbrand et al. 1995; Jongman, Wayland, and Wong 2000; McMurray and Jongman 2011; Newman, Clouse, and Burnham 2001). For vowels this can be largely attributed to differences in vocal tract length, but not entirely (Bladon, Gannon, and Pickering 1984; Johnson 2005; Johnson 2006). There appears to be less talker variability for stop voicing (e.g., /b/ vs. /p/), and little systematic effect of sex (Allen, Miller, and DeSteno 2003; Lisker and Abramson 1964; Chodroff et al. 2015). Despite differences in the overall degree of talker variability, there is stylistic variation in both which cannot be reduced to physiological differences. For instance, regional dialects of American English differ in their pronunciation of vowel categories (Clopper, Pisoni, and Jong 2005; Labov, Ash, and Boberg 2005). Use of voice onset time (VOT) as a cue to stop voicing varies based on language background (e.g., monolingual English speakers vs. French bilinguals; Caramazza et al. 1973; Flege 1987; Pineda and Sumner 2010; Sumner 2011), as well as regionally in the UK (Docherty et al. 2011).

We also know that listeners use socio-indexical group information to guide speech recognition. Niedzielski (1999) found that if listeners believe that a talker is Canadian, they hear more Canadian raising than if they believe the talker is American. Hay and Drager (2010) found a similar sensitivity to dialect group using an even subtler manipulation, manipulating listeners perceptions based on a stuffed animal that cued New Zealand or Australia. Perception of vowels and fricatives is affected by the perceived gender of a talker, which can be cued by voice quality, visual presentation of a male or female face, or even explicit instruction (Strand 1999; Johnson, Strand, and D’Imperio 1999; Strand and Johnson 1996). Indirect evidence that listeners are sensitive to socio-indexical grouping variables comes from recalibration (also known as perceptual learning) studies that show different patterns of generalization from male to female talkers (and vice-versa) for different cues/contrasts (Eisner and McQueen 2005; Kraljic and Samuel 2005; Kraljic and Samuel 2007; Reinisch and Holt 2014).

Finally, there is evidence that listeners can *infer* socio-indexical variables based on speech, but it’s not clear what linguistic variables they use (for a review, see Thomas 2002). Of particular interest, listeners can classify talker’s regional dialect at above-chance accuracy based on a short excerpt of their speech (a single sentence read from a standard set Clopper and Pisoni 2006; Clopper and Pisoni 2007). There is also evidence that listeners can infer talker *identity* from sine-wave speech (Remez, Fellowes, and Rubin 1997), speech which has been processed to remove most non-phonetic voice quality cues to identity but preserve most phonetic information (Remez et al. 1981).

## Methods

We next describe the datasets we use and the motivations for selecting these datasets. Then, we introduce our methods for quantifying informativity, utility, and inferrability of socio-indexical grouping variables. Finally, we discuss technical considerations.

<sup>1</sup>For the current study, we restrict ourselves to English, and focus primarily (but not exclusively) on *American* English.

## Data

We analyze speech from two corpora, one focusing on vowels and the other on stop consonant voicing. One goal of this paper is to compare the informativity and utility of socio-indexical grouping variables *between* different phonetic contrasts and cues. Our selection of datasets is guided by this goal. Stop voicing (cued by voice onset time (VOT) and vowel identity (cued by formant frequencies) have markedly different patterns of talker variability. Thus, we expect that comparing them will provide a good estimate of the range of informativity and utility of socio-indexical grouping variables across phonetic contrasts.

Our methods for assessing informativity and utility of grouping variables also constrain our choice of datasets, in two main ways. First, in order to assess informativity about cue distributions, we need enough tokens of each category from each talker in order to estimate these distributions. Second, to assess group-level utility for speech recognition, we need tokens from each phonetic category *within* talker (or at least within group).

## Vowels

For vowels, we used data from the Nationwide Speech Project (Clopper, Pisoni, and Jong 2005). Specifically, we analyzed first and second formant frequencies (F1xF2, measured in Hertz) recorded at vowel midpoints in isolated, read “hVd” words. This corpus contains 48 talkers, 4 male and female from each of 6 regional varieties of English: North, New England, Midland, Mid-Atlantic, South, and West (see map in Clopper, Pisoni, and Jong 2005; regions based on Labov, Ash, and Boberg 2005). Each talker provided approximately 5 repetitions of each of 11 English monophthong vowels (plus “ey”), for a total of 2659 observations.

One of our primary goals is to assess the informativity of different grouping variables. Sex differences in vocal tract size are a major source of variability in vowel production, and thus may be more informative than other factors. However, this likely depends on the details of how acoustic cues are represented. Differences in vocal tract size, for instance, lead to overall shifts in the resonant frequencies and hence formant frequencies across *all* vowels, but leave the relative positions of vowel categories more or less intact (e.g., Hillenbrand et al. 1995). Moreover, there is evidence that domain-general auditory normalization or adaptation processes removes some or all of this overall shift, and hence using un-normalized formant frequencies may overestimate the informativity of sex relative to other grouping factors.

For this reason, we also used Lobanov-normalized formant frequencies as input, in addition to the un-normalized formant frequencies in Hertz. Lobanov normalization z-scores F1 and F2 separately for each talker (Lobanov 1971), which effectively aligns each talker’s vowel space at its center of gravity, and scales it so they have the same size (as measured by standard deviation). This controls for overall offset in formant frequencies caused by varying vocal tract sizes (from both sex differences and individual variation). It does this while preserving the structure of each talker’s vowel space, so that (for instance) dialect-specific vowel shifts are maintained.

## Stop voicing

We analyzed data on word-initial stop consonant voicing in conversational speech from the Buckeye corpus (Pitt et al. 2007, extracted by Wedel, *in prep*). Voice onset time (VOT) was automatically extracted for 5984 word initial stops, 2264 voiced and 3720 voiceless, for labial, coronal, and dorsal places of articulation. Data came from 24 talkers, who were balanced male and female and younger/older than 40 years. On average, each talker produced 42 tokens for each phoneme (range of 5 – 156).

Our primary reason for considering VOT/voicing at all is to get a sense of the range of informativity and utility of socio-indexical variables across different phonetic categories. VOT is thought to be relatively stable across talkers, and formant frequencies relatively variable. The strength of this particular VOT corpus is that it contains observations of both voiced and voiceless stops from the same talkers. This allows us to directly assess how much talker variability in VOT distributions (Allen, Miller, and DeSteno 2003) ~~actually~~ impacts recognition of voiced vs. voiceless stops, and hence estimate an upper bound on the usefulness of *any* socio-indexical grouping variable for ~~this contrast~~.



However, the downside is that this corpus does not contain data from talkers who vary on socio-indexical variables that are known to correlate with differences in VOT distributions, like native language background. Preliminary analyses of a collection of VOTs for only voiceless stops from French-English bilinguals (Lev-Ari and Peperkamp 2013) suggests that, even though these groups are known to produce different VOT distributions, the size of this effect is much smaller than even talker-level variability *within* the monolingual talkers in the Buckeye corpus (which, to foreshadow our results, is substantially smaller than for vowels). Moreover, the addition of these talkers provides only a slight increase in the overall informativity of talker identity, compared to the monolingual talkers alone.



### Quantifying informativity, utility, and inferrability

Each phonetic category was modeled as a normal distribution: stop voicing as univariate distributions of VOT, and vowels as bivariate distributions of F1 and F2. We used the maximum likelihood estimators for the model parameters, which are the sample mean and covariance matrix.

For each socio-indexical grouping level, we trained separate models for each phonetic category based on all tokens from that category and grouping level (holding out test data when necessary, see below). The grouping levels we considered were

- Marginal (all tokens)
- Sex (male/female)
- Age (younger/older than 40, VOT only)
- Dialect (six regions, vowels only)
- Dialect+Sex (12 levels, vowels only)
- Talker



### Informativity with respect to cue distributions

In order to evaluate the *informativity* of socio-indexical variables with respect to cue distributions themselves, we use Kullback-Leibler (KL) divergence to measure how much group-specific cue distributions differ from the overall (marginal) cue distributions of each category.<sup>2</sup> If a socio-indexical variable is *not* informative about cue distributions, then the distribution for each level of that variable will be essentially identical, and hence indistinguishable from the *overall* distribution. If, on the other hand, a socio-indexical variable *is* informative about cue distributions, then the distribution for each group will deviate substantially from each other group, and by extension from the overall distribution as well. We do this separately for each linguistic category and group, and then average the results, calculating bootstrapped confidence intervals over groups.

The KL divergence of  $Q$  from  $P$  is  $DL(Q||P) = \int p(x) \log \frac{p(x)}{q(x)} dx$  (with density functions  $q$  and  $p$  respectively). In our case,  $P = \mathcal{N}_G$  is a multivariate<sup>3</sup> normal cue distribution ~~for the~~ group, with mean  $\mu_G$  and covariance  $\Sigma_G$ , while  $Q = \mathcal{N}_M$  is the marginal multivariate normal cue distribution with mean  $\mu_M$  and covariance  $\Sigma_M$ . With some simplification<sup>4</sup>, the KL divergence of the marginal from the group distribution works out to be

$$DL(\mathcal{N}_M||\mathcal{N}_G) = \frac{1}{2} \left( \text{tr}(\Sigma_M^{-1}\Sigma_G) + (\mu_M - \mu_G)\Sigma_M^{-1}(\mu_M - \mu_G) - d + \log \frac{|\Sigma_M|}{|\Sigma_G|} \right)$$

where  $d$  is the dimensionality of the distribution, and logs are natural logarithms (we report KL divergence in bits, which is the above quantity divided by  $\log(2)$ ).

<sup>2</sup>Technically, KL divergence is an information-theoretic comparison of two distributions. In our usage, it measures the expected cost (in bits of extra message length) of encoding data from each group using a code that's optimized for the marginal distribution.


<sup>3</sup>The math is the same for the univariate special case, as with VOT.

<sup>4</sup>See, for instance, [http://stanford.edu/~jlduchi/projects/general\\_notes.pdf](http://stanford.edu/~jlduchi/projects/general_notes.pdf), p. 13.





## Utility for speech recognition


Next, to address the *utility* of socio-indexical grouping for speech recognition, we calculate, for each level of socio-indexical grouping, the probability of correct recognition of phonetic categories. We do this using an “ideal listener” model (Clayards et al. 2008; Kleinschmidt and Jaeger 2015) that computes the posterior probability of a category given an observed cue value, given the distributions for each category. For instance, the probability that a particular F1xF2 value came from the /ae/ category is proportional to the probability (or *likelihood*) of that particular value being generated by the **ae** distribution, divided by its overall likelihood under all categories’ distributions. 

If two categories’ distributions overlap a lot, then they will frequently assign similar likelihood to cue values generated by the other, leading to confusion and recognition errors. ~~This is why correct recognition is~~ a measure of the utility of grouping. If lumping together tokens from, for instance, both male and female talkers causes vowel distributions to overlap more, that will decrease the probability of correct recognition, relative to the male- and female-only distributions (or distributions *conditioned on gender*).

More broadly, by calculating the probability of correct recognition using, for instance, the cue distributions of each category produced by female talkers, we can estimate how well a listener would be able to recognize speech from an unfamiliar female talker if all they knew was the talker’s sex.

Technically, we want to determine the phonetic category  $v_i^5$  of each of the cues  $x_i$  produced by a talker. If we assume that the listener knows that this talker belongs to group  $g = j$ , this inference is a straightforward application of Bayes Rule:

$$p(v_i|x_i, g = j) \propto p(x_i|v_i, g = j)p(v_i)$$

If, on the other hand, the listener does not know which group the talker belongs to, they have to marginalize  out group. This amounts to taking a weighted average of the posterior probabilities under each group, weighted by the probability that the talker belongs to that group,  $p(g|x)$  (which we compute below):

$$p(v_i|x_i) = \sum_j p(v_i|x_i, g = j)p(g = j|x)$$

(where  $x$  refers to all the tokens produced by this talker).



For vowels, we classified vowel categories directly. For voicing, the only cue available is VOT, which does not (reliably) distinguish place of articulation. Thus, we classified voicing separately for each place of articulation, and then average the resulting accuracy.

## Inferability of socio-indexical groups

Finally, to address how much cue distributions tell listeners about socio-indexical variables themselves, we **classify each talker’s socio-indexical group (at each level)**. This provides a measure of how well a listener would be able to determine, for instance, whether a talker was male or female based only on the distributions of cues they produce (even without knowing the intended category of each production).

As for speech recognition, we use an ideal observer model. That is, we compute the posterior probability of each socio-indexical group  $g = j$ , given all of the talker’s observed cue values  $x$ :

$$p(g|x) \propto p(x|g)p(g) = \left( \prod_i p(x_i|g) \right) p(g)$$

The only complication is that, without knowing the the phonetic category of each observation a priori, each observation may have been generated by any of the phonetic categories. Thus, to determine the *overall*

<sup>5</sup> $x_i$  refers to a single observed cue value (possibly multidimensional, ~~in~~ the case of vowel formants), and  $x$  (without subscript) refers to a *vector* of multiple observations (from a single talker, unless otherwise specified).  $v_i$  refers to observation  $i$ ’s category, and  $g$  to a talker’s group.  $\sum_j$  refer to a sum over all possible values of  $j$ .



likelihood of observing a cue value  $x_i$  under group  $g$ , we first have to marginalize over categories  $v_i$ :

$$p(x_i|g) = \sum_k p(x_i|v_i = k, g)p(v_i = k|g)$$

For all of these classifications, we assume a flat prior on categories/groups. We perform this analysis separately for each level of socio-indexical grouping. For instance, we compute both  $p(\text{sex}|x)$  and  $p(\text{dialect}|x)$  for each talker.

## Technical modeling considerations

We use a bootstrapping procedure to assess group differences and calculate confidence intervals for our estimates of utility, informativity, and inferability. In general, we resample talkers, in order to estimate the population-level variability from the limited sample of talkers in our datasets. However, for informativity, we have a single observations from each group (not talker), and so we resample groups instead.<sup>6</sup> For testing group differences, we use the proportion of resampled datasets with same-sign difference as the bootstrapped  $p$  value.

## Avoiding anti-conservative estimates through cross-validation

For classification, if test data is included in the training set, this artificially inflates accuracy at test (James et al. 2013, Section 5.1). Cross-validation controls for this by splitting data into training and test sets. For group-level models (sex, age, dialect, and dialect+sex), we use leave-one-talker-out cross-validation: train each group’s models with test talker’s observations held out. For the talker-specific models, we use 6-fold cross-validation (or leave-one-out when there were fewer than 6 tokens in a category for a talker), where each phonetic category is randomly split into 6 approximately equal subsets. Then, one subset of each category is selected for test, the models are trained on the remaining five, and the test data is classified as above.

Cross-validation is not only important because it provides an unbiased measure of classifier accuracy. It is also essential for testing the hypothesis that *group-level* cue distributions are useful to listeners. If the test talker is included in the training dataset, then the utility of that talker’s own productions is confounded with any utility of the group itself.

## Avoiding biases from differing group sizes

For the vowel data, the different levels of grouping have very different group sizes, and this requires some caution. The broadest (sex) has 24 talkers per group (23 after holdout), while the most specific (dialect+sex) has only 4 (3 after holdout). This introduces a systematic bias in favor of broader groupings, because small sample sizes lead to noisier estimates of the underlying model, and hence lower accuracy (on average) at test (James et al. 2013, Section 2.2). To correct for this, ~~after holding out the test talker~~, we randomly subsampled talkers (without replacement) within each group in the training set to be the same as the smallest group (3 talkers, based on Dialect+Sex<sup>7</sup>).

We use 20 different random subsamples for each test talker, averaging accuracy over each resampled training set. A different subsampling is used for every talker, and thus any additional variance introduced by this procedure is accounted for by bootstrapping talkers. The estimates obtained in this way allow us to compare accuracy across groupings with different group sizes, but at the cost of underestimating the true group-level accuracy across the board. As such, they must be considered a useful lower bound on the utility of socio-indexical groupings.

<sup>6</sup>While it’s possible to resample talkers before calculating the KL divergence of group-level distributions from marginal, this systematically increases the KL divergence. The reason for this is that in bootstrapping, talkers are resampled with replacement, which means that the variance of the resulting resampled group-level distributions goes down, increasing the KL divergence from the (already higher variance) marginal distributions.

<sup>7</sup>We also ran the analyses resampling each group to 7 talkers, which corresponds to the Dialect-level group size after holdout (excluding the Dialect+Sex grouping, since there are only 4 talkers per group before holdout). Besides a small increase in overall accuracy (because of the reduced variance of the distribution estimates), this did not substantially change the results.

## Results

### Informativity of socio-indexical groupings about cue distributions

We first analyze how informative each socio-indexical grouping variable is about the cue distributions of each phonetic category. As described in the methods, we measure informativity by the average KL divergence between the group-conditional cue distributions and the unconditioned (marginal) cue distributions.

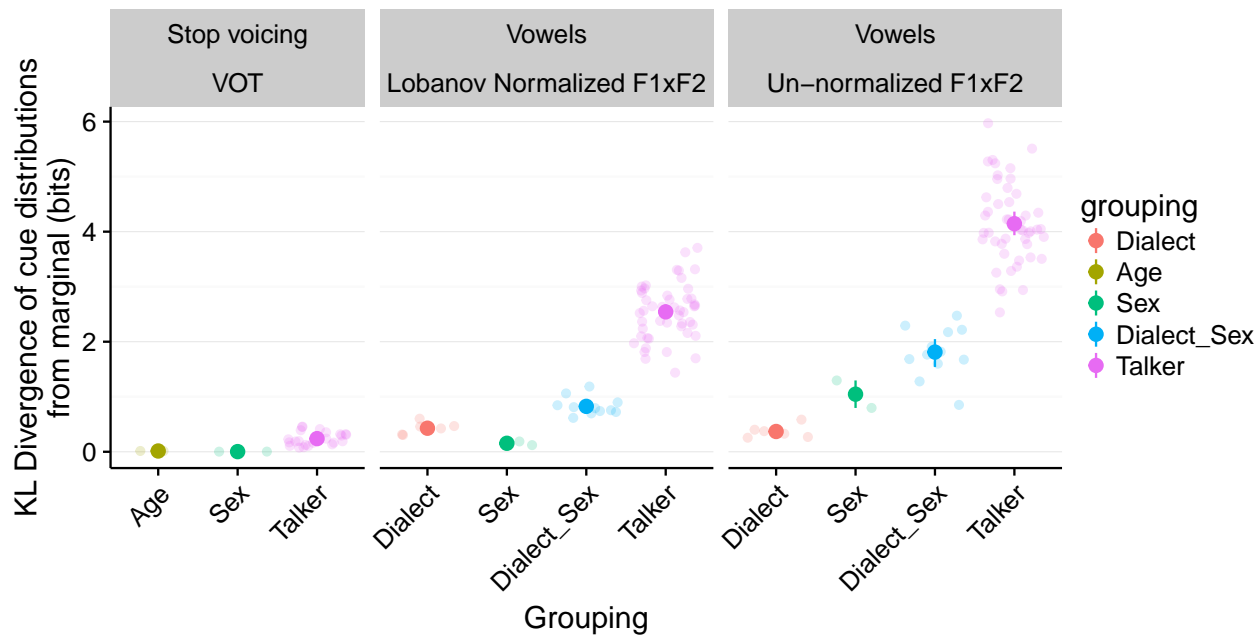


Figure 1: Socio-indexical variables are more informative about cue distributions for vowel (formants) than for stop voicing (vot). On top of this, more specific groupings (like Talker and Dialect+Sex) are more informative than broader groupings (Sex). This is indicated by higher KL divergence of each grouping level from marginal (showing mean and 95% bootstrapped CIs over groups).

Figure 1 plots the KL divergence of cue distributions at different levels of grouping from marginal distributions, across contrasts (vowels and stop voicing) and cues (vot, raw/Lobanov-normalized F1xF2). There are two clear patterns.

First, socio-indexical variables are in general more informative for vowels than for stop voicing, even using normalized formants as input. Strikingly, the *most* informative variable for VOT—talker identity—is roughly as informative as the *least* informative variable for Lobanov-normalized F1xF2 (Sex). As Figure 2 shows, this means that, on average, individual talkers’ VOT distributions diverge from the marginal distribution (B) at roughly the same level that the male and female distributions of normalized F1xF2 diverge from the marginal normalized F1xF2 distributions (A).

Second, there are substantial differences in the informativity of the socio-indexical grouping variables we considered. The overall pattern is that more specific grouping factors are more informative than broader groupings. The notable exception to this pattern is the Sex is the most informative variable for un-normalized F1xF2 distributions, which reflects the fact that overall sex differences explain much (but not all) of the talker variation in F1xF2 (Hillenbrand et al. 1995; Johnson 2006).

As Figure 3, while the relative ordering of grouping variables’ informativity is consistent across vowels, their actual degree of informativity varies quite a bit. Dialect (and Dialect+Sex) is particularly informative for *aa*, *ae*, *eh*, and *uw*, vowels with distinctive variants in at least one of the dialect regions from the NSP. *aa* is undergoing a merger with *ao* in some regions, *ae* and *eh* participate in the northern cities chain shift, and *uw* is fronted in some regions (and in others, but only by female talkers; Clopper, Pisoni, and Jong 2005).



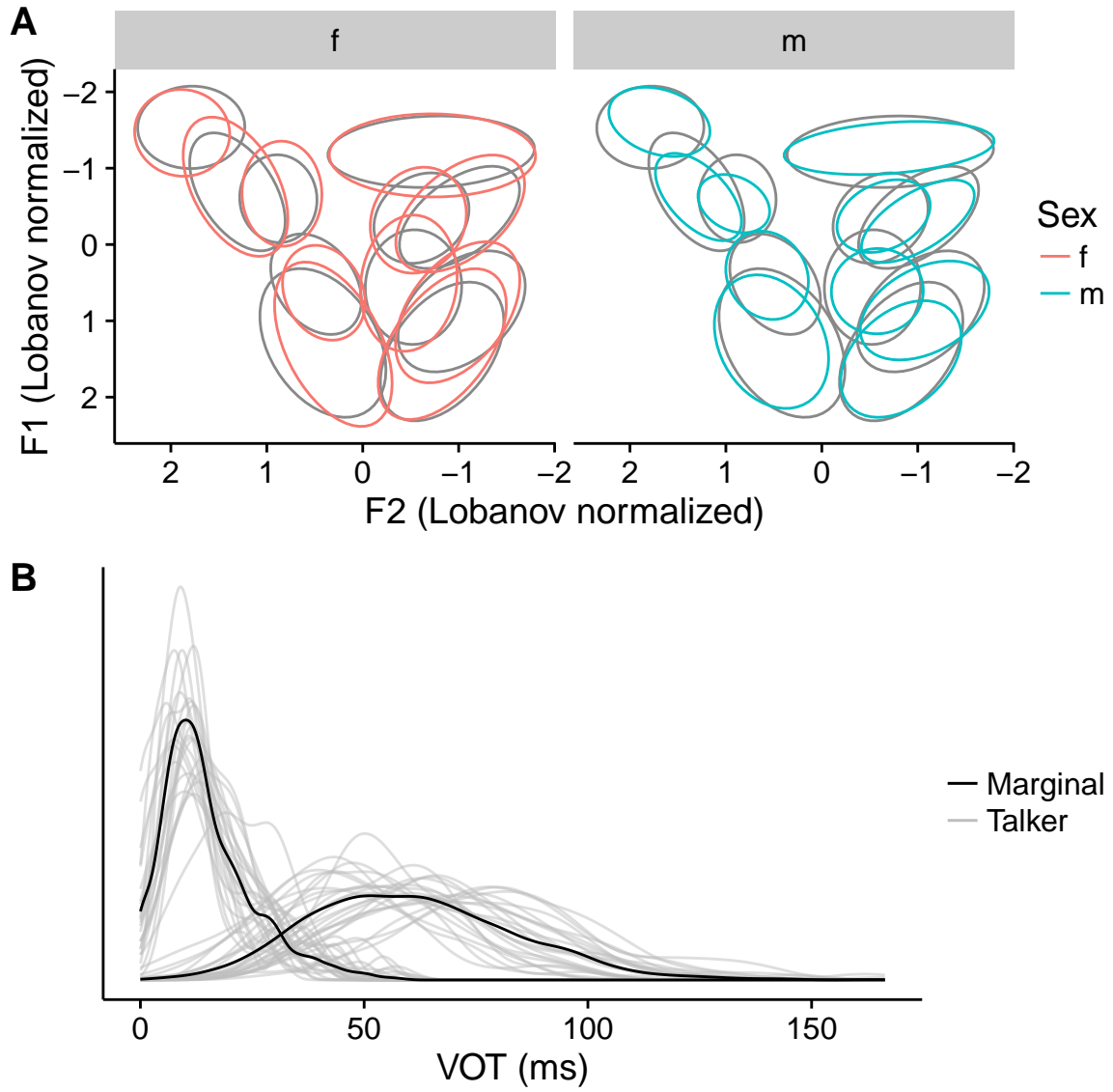


Figure 2: Male and female distributions of Normalized F1x2 diverge from the marginal distributions (A) only slightly less than talker-specific VOT distributions diverge from marginal (B).

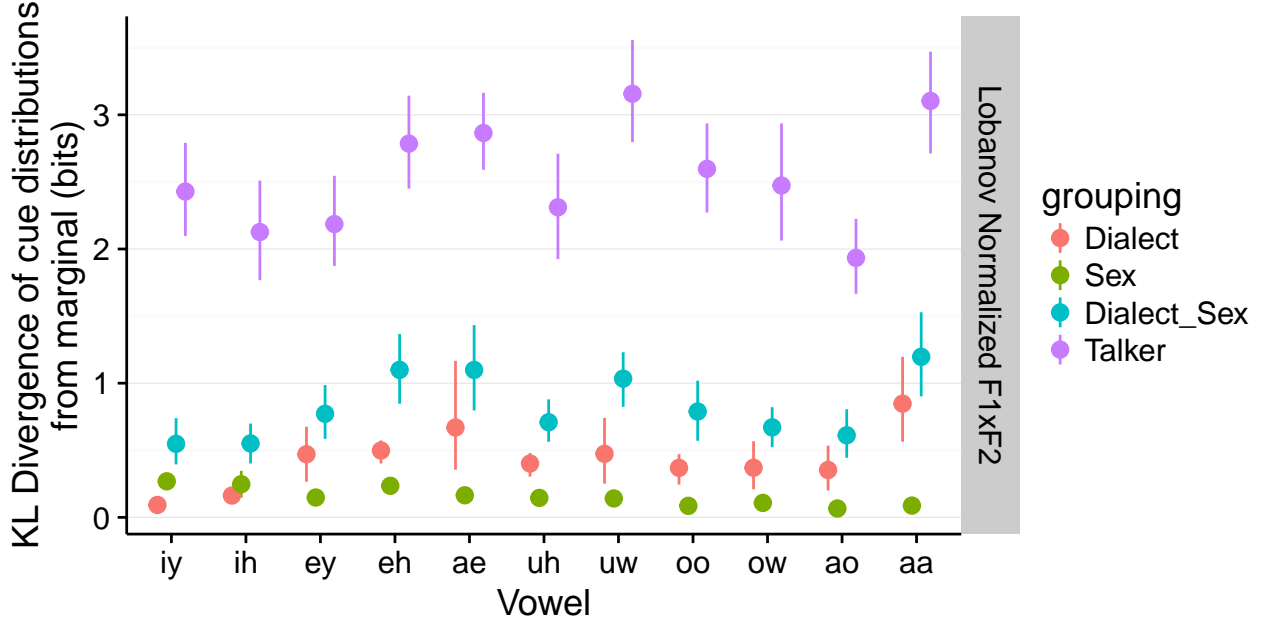


Figure 3: Individual vowels vary substantially in the informativity of grouping variables about their cue distributions. Only normalized F1xF2 is shown to emphasize dialect effects.

Finally, individual dialects also vary in how informative they are about vowel formant distributions. Figure 4 shows that talkers from the North dialect region produce vowels—**ae** and **aa** in particular—with formant distributions that deviate markedly more from the marginal distributions than any of the other dialects. Other dialects have, on average, similar deviations from marginal. The high deviation of **uw** by New England talkers is the result of these talkers producing a very low-variance, back (low F2) distribution. Similarly, Mid-Atlantic talkers produce a low-variance **ey** distribution that is higher and fronter than average. Finally, the Mid-Atlantic **aa** is, like the Northern **aa**, non-merged with **ao** (Clopper, Pisoni, and Jong 2005) and hence deviates from the marginal **aa** substantially.

### Utility of socio-indexical groupings for speech recognition

Next, we evaluate the *utility* of each grouping variable for speech recognition. The utility of a grouping variable—like dialect—can be quantified as the probability of correct recognition given the cue distributions conditioned on each group—e.g., each dialect—using an ideal listener model (Clayards et al. 2008; Kleinschmidt and Jaeger 2015).

Figure 5 shows the probability of correct recognition for stop voicing/vowel, based on the cue distributions at each level of grouping. As with informativity about the distributions themselves, there’s an asymmetry between vowels and stop voicing in the overall utility of socio-indexical variables for speech recognition. Probability of correct recognition is overall higher for stop voicing than vowels. Voicing recognition is also less sensitive to the particular grouping variable, which is consistent with the finding above that VOT distributions do not differ substantially at different levels of socio-indexical grouping. There is, however, a slight advantage for using talker-specific VOT distributions for recognition, over marginal, age-, and sex-conditional distributions (on the order of 2% increase in accuracy, all three  $p < 0.01$ ).<sup>8</sup>

Normalized input results in higher vowel recognition accuracy across the board, again paralleling the findings about the cue distributions themselves. The one exception is at the level of talker-specific distributions, where recognition accuracy is unchanged (since Lobanov normalization is a linear transformation of the input, which leaves the structure of the categories within each talker unchanged).

<sup>8</sup>These comparisons are also significant when using log-odds of correct recognition, rather than raw probabilities.

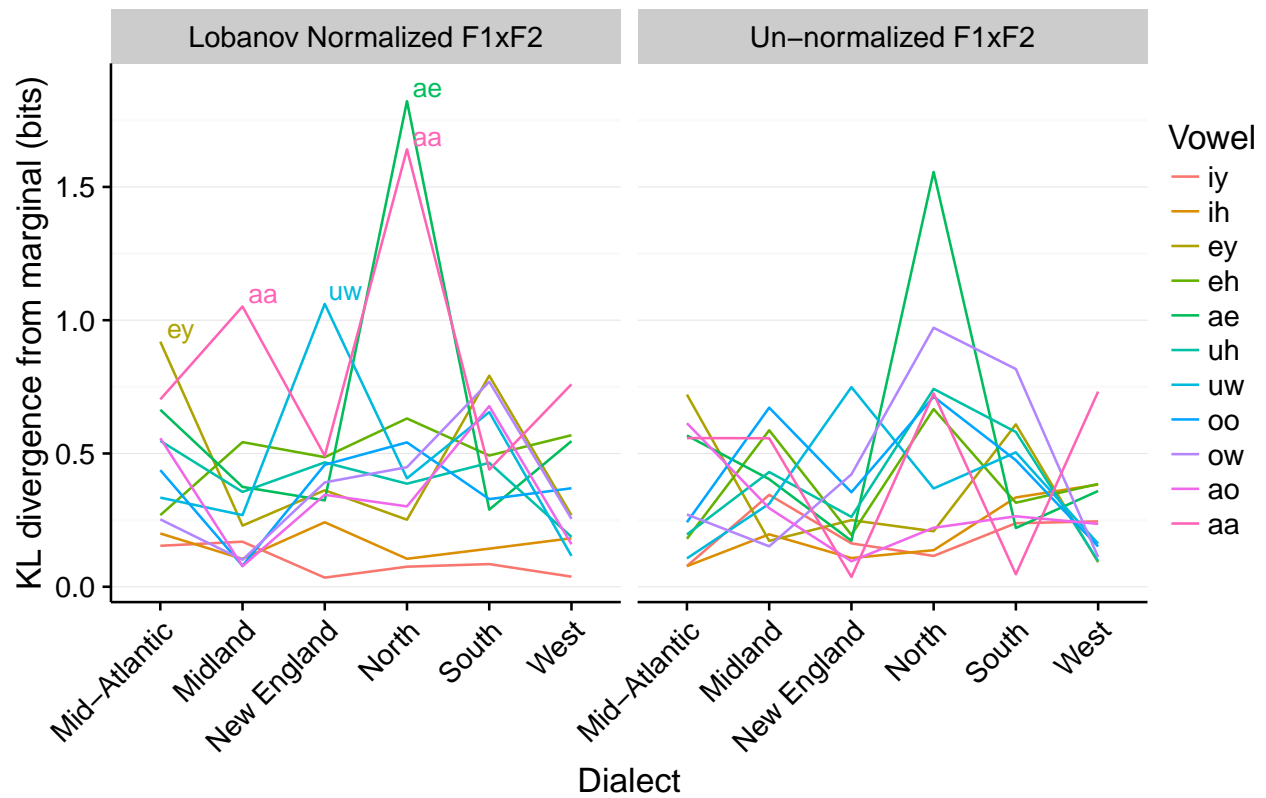


Figure 4: A small number of dialect/vowel combinations account for most of the divergence of dialect-specific vowel formant distributions. In particular, the distribution of **ae** and **aa** produced by Northern talkers diverge markedly more than any other vowel/dialect combination.

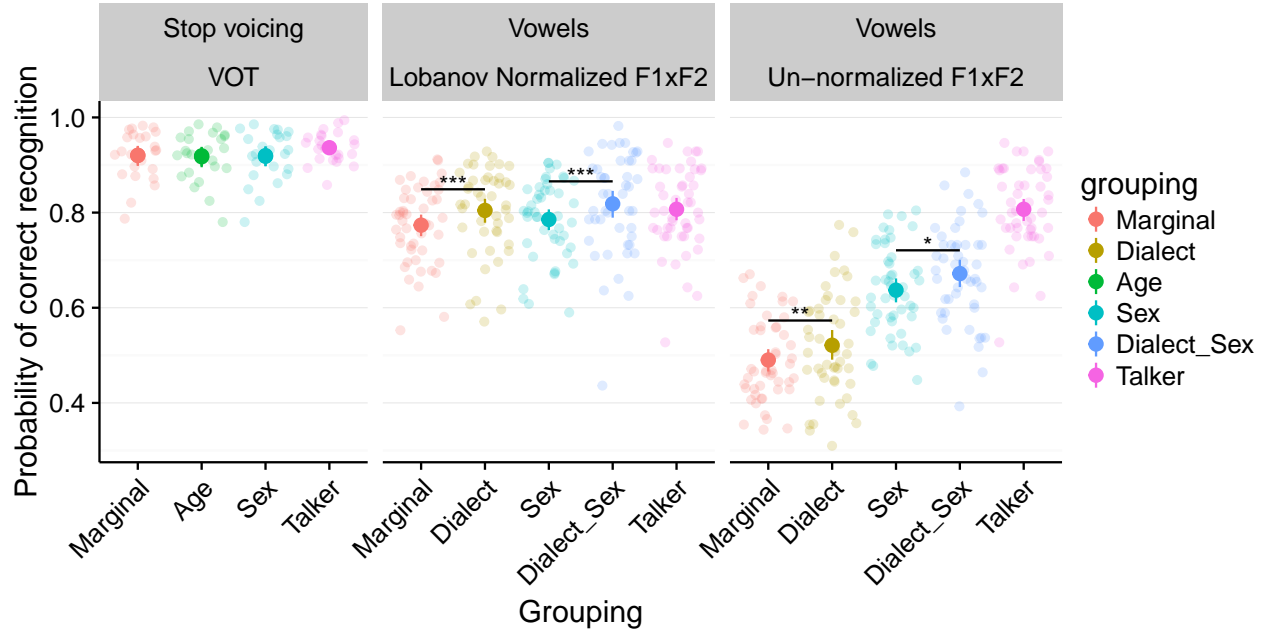


Figure 5: Speech recognition accuracy using for marginal, group-level, and talker-specific cue distributions. Small points show individual talkers, and large points and lines show mean and bootstrapped 95% CIs over talkers. Marginal and group-level accuracy is based on leave-one-talker out cross-validation, and talker-specific on 6-fold cross-validation (or leave-one-token-per-category out if there are fewer than 6 tokens per category). Bars and stars show significant increases in accuracy when conditioning on dialect, alone or in addition to sex. Here and elsewhere: \*  $p < 0.05$ , \*\*  $p < 0.01$ , and \*\*\*  $p < 0.001$ .

Also paralleling the cue distributions themselves, classifying according to sex-specific distributions provides the biggest boost in recognition for un-normalized formant accuracy. For normalized input, none of the socio-indexical grouping factors provide much of an advantage over the marginal distributions. In both cases, dialect provides a small but consistent advantage for recognition, both alone and in combination with sex (increasing accuracy by 3% on average, all  $p < 0.05$ ).

The utility of socio-indexical grouping for recognizing individual vowels largely mirrors the overall pattern (Figure 6). The exception is that the utility of conditioning on dialect varies substantially from one vowel to the next. For most vowels, conditioning on dialect makes little difference to correct recognition. But for a few—particularly *ae* and *eh*—conditioning on dialect increases accuracy by nearly 10%. In the case of normalized formant input, accuracy using dialect-conditioned distributions actually equals or surpasses the accuracy with talker-specific distributions.

The overall utility of dialect also varies substantially based on the talker’s actual dialect (Figure 7). This is consistent with the fact that dialects themselves vary in how much they deviate from both the norms of Standard American English (Clopper, Pisoni, and Jong 2005) and from the marginal cue distributions in this dataset (Figure 4). Most notably, conditioning on dialect provides a consistent advantage for talkers from the North dialect region, on the order of 10%.

### Inferring socio-indexical variables from cue distributions

Finally, we assess how well listeners could infer socio-indexical variables from unlabeled acoustic-phonetic cues, based on the group-conditional cue distributions. We measure this by the accuracy with which an “ideal listener” can categorize a talker’s group membership for each socio-indexical grouping variable.

For most groupings, it is possible to infer each talker’s group with above chance accuracy, given only that

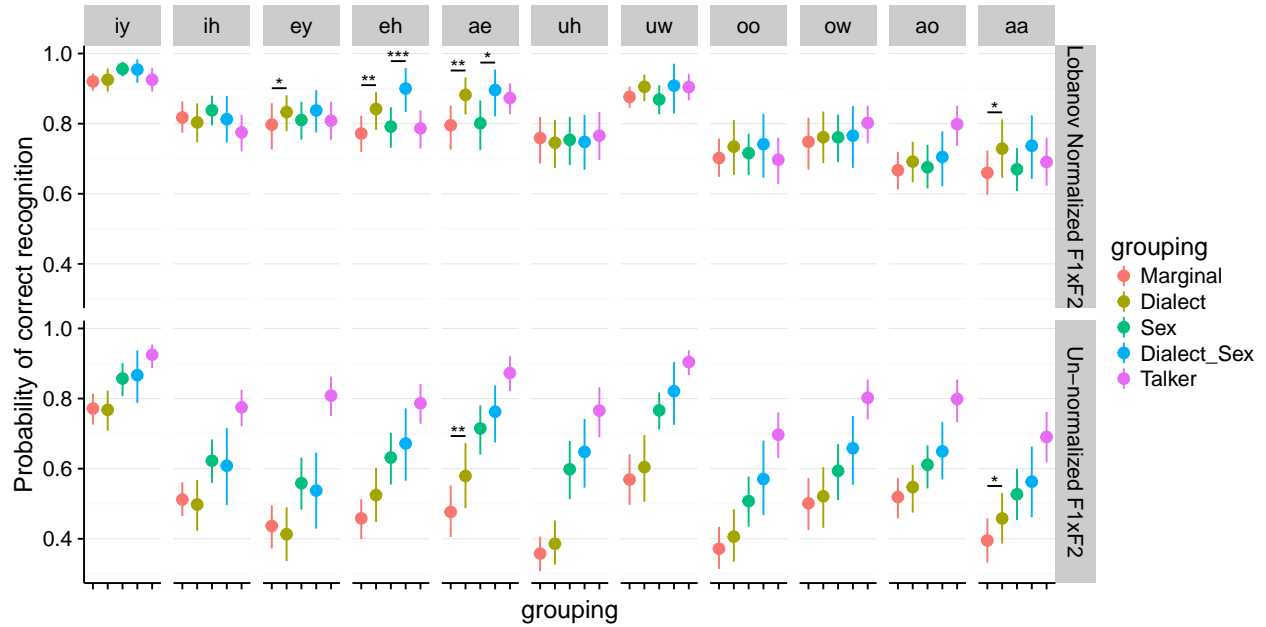


Figure 6: Probability of correct recognition varies across vowels, overall and according to the socio-indexical grouping variable. Bars and stars show significant improvement from conditioning on dialect, above marginal or in addition to sex alone.

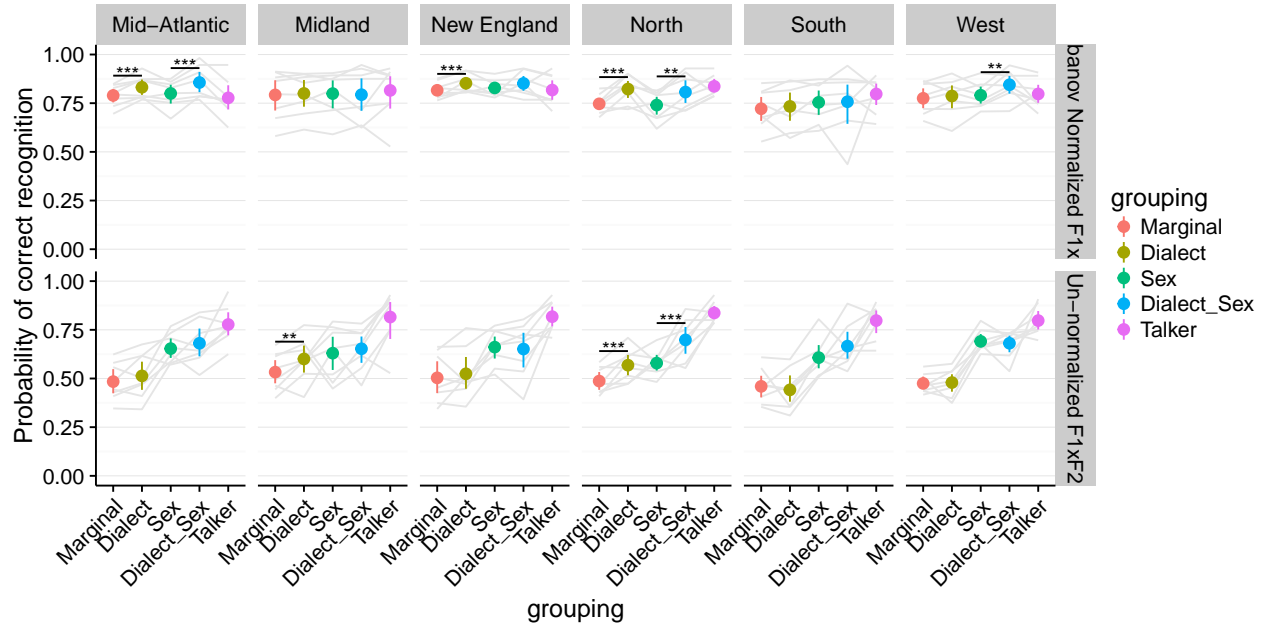


Figure 7: The utility of socio-indexical variables varies across dialects. Dialect itself is particularly informative only for talkers from the Mid-Atlantic and North regions. Each line shows a single talker, to emphasize within-talker changes in accuracy with grouping level, and large points and confidence intervals show mean accuracy and bootstrapped 95% CIs over talkers.

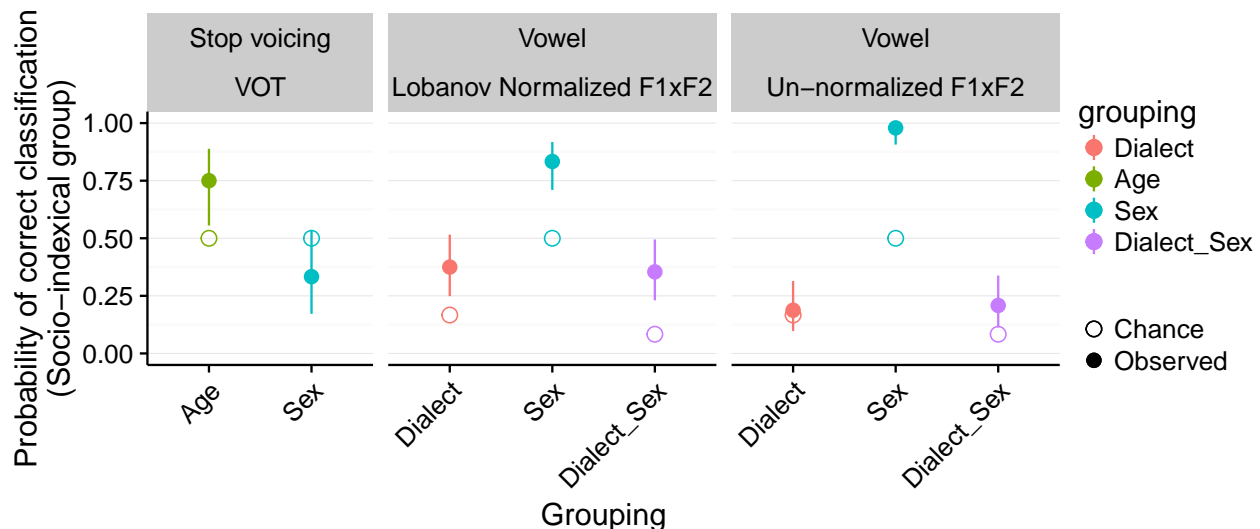


Figure 8: Probability of correctly classifying a talker’s socio-indexical group varies with the grouping variable, contrast, and cues. A talker is correctly classified if the overall posterior probability of their actual group given their unlabeled productions is the highest of all groups.

talker’s unlabeled observed cues (Figure 8; all  $p < 0.01$ , except for inferring a talker’s sex based on their VOT distributions, and dialect from un-normalized F1xF2 distributions, both  $p > 0.15$ ).

In some respects, these results mirror the patterns of informativity about the cue distributions themselves (Figure 1). Vowel formant distributions vary more according to group than do stop VOT distributions, and likewise socio-indexical group can, on the whole, be inferred with higher accuracy based on vowel formants than on VOT. For vowels specifically, much of the variability across talkers is driven by sex differences, and this is the grouping variable that’s easiest to infer of the three we tested.

However, in other respects, these results do *not* simply mirror informativity. For instance, un-normalized F1xF2 distributions diverge from marginal more for dialect+sex than they do for sex alone, but accuracy at inferring a talker’s sex is nearly at ceiling, while accuracy is barely above chance for inferring a talker’s dialect+sex. Likewise, normalized F1xF2 distributions given dialect and dialect+sex diverge from marginal less than non-normalized, but accuracy at inferring these two grouping variables is higher for normalized than non-normalized.

Why the discrepancy? The informativity measure we used was the average divergence of *each category’s* cue distribution. For inferring indexical groups, we assumed that listeners do not know the intended category of each observation, and so the relevant likelihoods are each based on a *mixture* of the category-specific distributions. Even if there are some categories whose individual distributions diverge across groups, the overall mixture distribution of all categories may still be too similar to allow for the group to be reliably inferred.

## General Discussion

Our results show that, on the whole, socio-indexical grouping variables are *informative* about phonetic cue distributions, *useful* for improving speech recognition, and can be *inferred* from phonetic cues themselves. However, the extent to which these are true depends on the particular grouping variable and particular phonetic categories/cues involved. Socio-indexical variables are more useful, more informative, and more easily inferred for vowels than for stop consonant voicing. Some variables are broadly useful (sex, talker identity) while others are useful only in certain, specific contexts (dialect for certain vowels/dialect combinations).

Our results also speak to the relationship between informativity, utility, and inferrability themselves. In



general, informativity and utility mirror each other: conditioning on a socio-indexical variable is more useful for speech recognition when the corresponding conditional cue distributions diverge more from the overall or marginal distributions. But being useful for speech recognition does not always mean that a socio-indexical variable can be easily inferred from phonetic cues alone, or vice-versa.

Here we discuss the implications of these results. First, the ideal adapter generally predicts that listeners should track conditional distributions for groups that are informative and useful for speech recognition. By directly quantifying the utility and informativity of a number of grouping variables, our results are an important step towards making more specific predictions about what group-level representations listeners should maintain if, as assumed by the ideal adapter, they are taking advantage of the structure that is actually present in cross-talker variability. Second, our results shed light on discrepancies between phonetic contrasts in listeners’ willingness to generalize recalibration/perceptual learning from one talker to another. Third, this paper provides a proof of concept for the idea that, like phonetic judgements, socio-linguistic judgements can be productively viewed as a sort of inference under uncertainty. This suggests the potential for a tighter integration of sociolinguistic and psycholinguistic perspectives on speech perception.

## What to track?

Treating speech perception as a problem of inference under uncertainty—as the ideal adapter does—highlights the importance of listeners’ knowledge about the distributions of cues that are produced for each linguistic unit. A major question that this perspective raises is *what* linguistic, socio-indexical, and acoustic/phonetic variables listeners are learning distributions for. The ideal adapter does not directly answer this question, but provides a set of conceptual and quantitative tools for addressing it. The studies reported here take these tools and apply them to data on how many different talkers produce two different sets of phonetic categories. We hope that by doing so we provide a proof of concept for the broad usefulness of these tools. One purpose they might be put to is to formulate hypotheses about what distributions listeners should track.

At the highest level, the ideal adapter predicts that listeners should not track *everything*. Rather, listeners need only track the joint distributions of variables that are informative. At the level of phonetic categories themselves, this means that (for instance) there’s no reason for listeners to track each vowel’s distribution of preceding VOT<sup>9</sup> (or more absurdly, completely unrelated physical quantities like temperature or barometric pressure). This also applies at the level of socio-indexical grouping variables: listeners get no benefit for tracking separate distributions for different groups of talkers for a cue that does not systematically vary between those groups.

In fact, it can actually *hurt* a listener to track cue distributions at a level that’s not informative. The reason for this is related to the idea of bias-variance tradeoff from machine learning (James et al. 2013, Section 2.2.2). Given the same amount of data, tracking multiple, specific distributions will result in noisier, less accurate estimates than lumping together all the observations in a single distribution. This price may be worth paying for a listener when there are large enough differences between groups that treating all observations as coming from the same distribution *biases* the estimates of the underlying distribution (and hence the inferences that listeners make based on those distributions) far enough away from the true structure of the data. To take a concrete example, modeling each vowel as a single distribution of (un-normalized) formants across all talkers results in high-variance, overlapping distributions which have low recognition accuracy. But modeling them as two distributions—one for males, and one for females—provides much more specific estimates and higher classification accuracy, as shown by Figures 1 and 5.

Thus, the ideal adapter predicts that listeners should learn separate cue distributions for levels of a socio-indexical grouping variable when that variable has high *informativity* about some categories’ cue distributions and/or high *utility* for speech recognition. However, the notions of informativity and utility apply beyond better *speech* recognition per se. Listeners extract a lot of non-phonetic/linguistic information from speech signal. To properly define the informativity or utility of a particular grouping variable, we need to consider the *goals* of speech perception, which go beyond just recognizing phonetic categories. Sociolinguistics

<sup>9</sup>Barring, of course, the possibility that VOT is systematically affected by neighboring vowels, and hence informative about them.

recognizes that, in many cases, the communication of social information is just as if not more important than the communication of linguistic information. Groupings that are *socially meaningful* can thus be informative and justify being tracked, even if ignoring them has a negligible effect on speech recognition, as long as the corresponding cue distributions carry some information about relevant social variables. In our results, dialect is a good example: on the whole, ignoring dialect doesn't have huge consequences on recognition accuracy. But it can be inferred (at least above chance) based on vowel F1 and F2, and listeners are plausibly interested in determining a talker's regional origins for a variety of reasons.

An additional consideration is that listeners are not simply told which variables are informative and which are not. They must actually *infer* what distributions are actually worth tracking. Moreover, every listener's experience with talker variability will be different, and so a variable that is informative in one listener's experience may be irrelevant in another's. While the analyses we present here go a long way toward focusing the predictions of the ideal adapter framework, they must be combined with knowledge of each listener's own personal history—either assumed, or somehow measured, even approximately—in order to make specific predictions for a particular subject or population of subjects. This same logic applies to which socio-indexical variables are of direct interest to a listener: social categories that are highly important in one person's social world may be completely meaningless in another's. An important aspect of the research program laid out by the ideal adapter framework is to probe listeners' prior beliefs *directly* (which the previous chapter is a first step towards)

Finally, our results suggest that the input representation—the cue space over which categories are distributions—can affect which variables are informative or not. For vowels, using Lobanov-normalized formants as input substantially reduces the informativity and utility of sex as a grouping factor, but *increases* the utility of dialect in many cases. From a listener's perspective, dialect would appear to be relatively uninformative without normalization. This points to a complex interaction between normalization and adaptation/perceptual learning as strategies for coping with talker variability. Both strategies are, in fact, used by listeners, but the interaction between them is poorly understood (Weatherholtz and Jaeger 2016).

## Consequences for adapting to unfamiliar talkers

The results of this study also tell us something about how listeners might adapt to an unfamiliar talker. The ideal adapter links informativity to adaptation, and the results here allow us to make more specific predictions based on the ideal adapter, in two ways.

First, the informativity of talker identity is a measure of the variability across talkers. When talker identity is highly informative, there's more variability across talkers, and the ideal adapter predicts that prior experience with other talkers will be less relevant, resulting in faster and more complete adaptation to an unfamiliar talker. We found here that talker identity is less informative about VOT distributions than it is for vowel formant distributions. Hence, the ideal adapter predicts that listeners will adapt to talker-specific VOT distributions more slowly, and be more constrained by prior experience with other talkers. The first prediction is borne out by Kraljic and Samuel (2007), who compared recalibration of a voicing contrast with a fricative place contrast. It's also borne out indirectly by the modeling work in Chapters NNN and NNN, which found that the effective prior sample size for /b-/d/ (which, like vowels, is primarily cued by formant frequencies) is much lower than for /b-/p/ (cued by VOT).

Second, the informativity of higher-level grouping variables is linked to *generalization* across talkers: if two talkers are from groups that tend to differ, listeners should treat them separately and not generalize from experience with one talker to the other. Likewise, if two talkers are from the same group, listeners *should* generalize. We found that talker sex is informative for vowel formant distributions, but not for VOT, which means that listeners *should* generalize from a male to a female talker (and vice-versa) for a voicing contrast, but *not* for a vowel contrast. Listeners do, in fact, tend to generalize voicing recalibration across talkers of different sexes (Kraljic and Samuel 2006; Kraljic and Samuel 2007). While there's (to our knowledge) no data on cross-talker generalization for vowel recalibration, listeners tend not to generalize across talkers for fricative recalibration (Eisner and McQueen 2005; Kraljic and Samuel 2007), which (like vowels) are cued

by spectral cues that vary across talkers and by gender (Newman, Clouse, and Burnham 2001; Jongman, Wayland, and Wong 2000; McMurray and Jongman 2011).

There is also evidence for the prediction of generalization *within* informative groups. In the absence of evidence that two talkers from the same group (e.g. two males) produce a contrast differently, experience with one provides an informative starting point for comprehending (and adapting to) the other. Along these lines, Zande, Jesse, and Cutler (2014) found that listeners generalize from experience with one male talker’s pronunciation of a /b/-/d/ contrast to another, unfamiliar male.

Finally, it’s important to point out that these predictions are best thought of as *biases* that can be overcome with enough of the right kind of evidence (Kleinschmidt and Jaeger 2015). For instance, listeners can overcome their bias to generalize experience with VOT and learn talker-specific VOT distributions, but it requires hundreds of observations from talkers who produce very different VOT distributions (Munson 2011). Likewise, listeners will generalize recalibration of a fricative contrast from a female to a male talker given the right kind of test stimuli (Reinisch and Holt 2014).

### Sociolinguistic inference

Our findings suggest that socio-linguistic judgements can—like linguistic judgements—be viewed as probabilistic inference. In this view, both social and linguistic judgements rely on knowledge of how different underlying categories—social and linguistic—are probabilistically realized as distributions of observable cues. Just like each vowel (for instance) is realized as a distribution of F1 and F2 values, each dialect is *also* realized as an F1xF2 distribution (along with many other cues). When a listener hears a talker produce particular cue values, they can use knowledge of these distributions to compare how well each possible underlying social variable *explains* the speech they’ve observed. We find that this kind of model can classify a talker’s dialect at roughly the same accuracy (10-40%) as human listeners in a forced-choice task based on sentences spoken by the same talkers (Clopper and Pisoni 2006).

The idea of socio-linguistic judgements of inference fits naturally within the ideal adapter framework, which holds that listeners are simultaneously making at least three kinds of inferences in the normal course of speech perception:

1. *What* a talker is saying
2. *How* that talker says things
3. *Who* that talker is, in relation to other talkers

The third level of inference is essential for talker-invariant speech perception: knowing *who* a talker is allows listeners to take advantage of their prior experience with other, similar talkers (Kleinschmidt and Jaeger 2015). Of course, listeners likely also want to know who a talker is for reasons that have nothing to do with accurate speech recognition per se. To the extent that a talker’s way of realizing linguistic variables says anything about who they are their speech is informative about their identity, at the same time as their identity is informative about their speech. Thus both sociolinguistic and psycholinguistic considerations lead to the idea that social inferences may well be inextricable from linguistic inferences.

Realizing that socio-linguistic judgements can be treated as a kind of inference is a potentially powerful idea, but it is important to realize that it is not, per se, a complete *model* of socio-linguistic judgements. Rather, it is a framework for developing such a model. In this view, the particular inferences that a listener would draw based on particular linguistic input depends not only on the distributions of cues in the world but just as much on the listener’s own, internal model of how social variables relate to each other. Or, as it’s more commonly put, a listener’s stereotypes or ideologies about language use and social identity.

Careful sociolinguistic work is required to tease these factors out. One example comes from Levon (2014). He finds that when UK listeners hear a male talker with high /s/ spectral center of gravity (COG), they infer that the talker is a gay man. But when they hear a male talker with high /s/ spectral COG *and* TH-fronting (i.e., /f/ for /TH/), they judge the talker to be a working class straight man. That is, the inference that the talker is working class *blocks* the inference that he is gay. These sorts of effects are perfectly compatible with an inference-based perspective, but they depend on the specific contents of the listeners internal model of

how social variables are related to each other and to observable cues (for examples in other domains, see R. A. Jacobs and Kruschke 2010). Such internal models are not directly derivable from production data like we analyze here, but rather require probing a listener’s subjective, implicit beliefs (as in the previous chapter).

## A lower bound

Finally, it is important to note that our results here constitute a *lower bound* on the informativity or utility of different levels of socio-indexical grouping.<sup>10</sup> We model cue distributions for a particular group as a *single* normal distribution over observed cue values. In reality, a hierarchical model is more appropriate, since different levels of grouping can nest within each other. For instance, each dialect group is likely better modeled as a *mixture* of talker-specific distributions, which each exhibit dialect features to a varying degree. This is especially important for *adaptation* to an unfamiliar talker, since a group-level distribution conflates *within* and *between* talker variation, both of which have separate roles to play in belief updating.

The approach to group-level modeling that we take here is roughly equivalent to the *posterior predictive* distribution of a fully hierarchical model, which integrates over lower levels of grouping to provide a single distribution of cues given the group (and phonetic category). This corresponds to the best guess a listener would have *before* hearing anything from an unfamiliar talker, if the only information they had about that talker was their group membership. As the listener hears more cue values from the talker, the hierarchical nature of grouping structure becomes more important and can provide (in principle) a significant advantage over what we measured here. But modeling this process is quite a bit more complicated and we leave it for future work. Nevertheless, modeling each category as a single, “flat” distribution per group may well prove a useful approximation, or even a boundedly-rational model of how listeners take advantage of different levels of grouping structure (and similar approaches have been used in, e.g., motor control Körding et al. 2007).

## Conclusion

Socio-linguistic variables like age, sex, and regional origin have been identified by sociolinguistics as factors that systematically affect the realization of linguistic categories. Using an ideal observer framework, we quantified the extent to which a range of these variables are *informative* about the distributions of acoustic cues corresponding to linguistic categories, *useful* for recognizing those categories, and can themselves be *inferred* from unlabeled cues. Our results show that the utility and informativity of a particular socio-indexical variable are closely related but not identical, while inferrability is distinct. Moreover, we demonstrate how this method for quantifying these factors allows them to be compared across phonetic categories as well as cues/contrasts (VOT vs. F1xF2).

Together, these results show that the idea of inference under uncertainty, when applied to speech perception, provides a unifying perspective on both linguistic and socio-linguistic perception. This perspective leads to conceptual and computational tools for addressing questions that are of interest to psycholinguistics and sociolinguistics, as well as developing new bridges between the two.

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<sup>10</sup>Even above and beyond the limitations imposed by unequal numbers of talkers in each group, which necessitates subsampling talkers in the larger groups in order to meaningfully compare accuracy.

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