

Chapter 1

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): **because of noise in production processes**, 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). **As such, 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** : 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,  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** 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, **as we have alluded to**, is the *distribution* of cues **given different combinations of linguistic and indexical** *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 goals** of this paper, which **is** **are** 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:**

How informative are This paper is motivated by three interrelated questions about the relationship between socio-indexical **variables about the distribution of different acoustic-phonetic cues?** **How useful is** **variables** and phonetic categories/cues. **We next pose these questions,** before presenting the studies that **quantitatively** address each one in turn. **Together, these lay out** a novel, principled, and quantitative approach to understanding the relationship between socio-indexical **grouping for correct speech recognition?** **How well can you** variables and speech perception.

Question 1: how *informative* are socio-indexical variables about cue distributions?



Qualitatively, the structure of talker variation is different depending on the phonetic contrast and cues. ~~On the one hand,~~ vowels exhibit substantial variability conditioned on the gender and the regional background of the talker [Peterson and Barney (1952); Hillenbrand et al. (1995); Clopper2005; among others]. ~~On the other hand,~~ talker variation in word-initial stop voicing is largely unstructured, exhibiting little systematic variation by gender, regional dialect, or age (Allen, Miller, and DeSteno 2003; Chodroff et al. 2015). ~~But we don't know, quantitatively, the extent of these differences, beyond the existence of socio-indexically-conditioned variation in some cues/contrasts but not others.~~

~~At an even more basic level, we don't know whether the amount of talker variation is different. There's some suggestion that this might be the case:~~ visual inspection of the results of Chodroff et al. (2015) (Figure 1) suggests that cross-talker variance in voiceless word-initial stop VOT is roughly half of within-category variation (standard deviations of approximately 10ms and 20ms VOT respectively), whereas inspection of similar results for vowels from Hillenbrand et al. (1995) (Figure 4) suggests that cross-talker variability is easily *inferdouble* the within-category variability. Understanding these differences *quantitatively* is critical because the amount and type of talker variation places an upper bound on how informative socio-indexical variables *based on acoustic-phonetic cuedistributions alone?* can be for a particular phonetic category/cue.

We address these goals at different levels of In part, the lack of this information in the existing literature reflects the fundamental difficulty of comparing very different phonetic contrasts and cues. We address this here by testing how *informative* socio-indexical *grouping*, and for two different sets of phonetic cues/contrasts(vowels, variables—including talker identity—are about the distribution of acoustic-phonetic cues for two sets of contrasts/cues: vowels (cued by first and second formant *frequencies*, frequencies; F1xF2) and word-initial stop voicing, (cued by voice onset time, ; VOT). The Focusing on information theoretic properties of the cue distributions provides a principled common currency for comparing different 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. To anticipate our results, we find that the informativity and utility of socio-indexical variables differs substantially depending on the contrast, , phonetic categories, and particular way of representing input. cues. ~~We focus on these particular categories/cues because of the availability of suitable data, and because they both exhibit talker variability, but with different patterns of socio-indexically-conditioned variability in American English.~~¹



Finally, beyond connecting sociolinguistic and psycholinguistic perspectives on variability in speech perception, quantifying these relationships 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 conditional on a particular grouping variable (like 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 In order to address this question, we need data on contrasts/cues that might reasonably be expected to differ in the informativity of 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 drawvariables (including talker identity). As we summarized above, vowels and stop voicing are likely provide such a contrast, and thus we selected one corpus where the relevant cues were annotated for each.

Background



Question 2: How *useful* are socio-indexical variables for speech recognition?



¹One notable exception is native language background. For instance, French-English bilinguals produce significantly shorter VOTs than English monolinguals (Caramazza et al. 1973; Flege 1987; Pineda and Sumner 2010; Sumner 2011). The difficulty of finding suitable datasets on these talkers prevents us from considering this variable fully here, but preliminary analysis of VOT distributions (from Lev-Ari and Peperkamp 2013) suggest that they would not substantially change our conclusions.

What do we already know about the relationship between speech perception and socio-linguistic variables?²

First, we know that the *amount* and *structure* of talker variability differs between cues and phonetic categories. Vowels and fricatives have a lot of From the perspective of speech perception, 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, Henton, 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 is a problem, because it can interfere with linguistic judgements. One of the insights of the ideal adapter is that the extent to which talker variability is a problem—and how much grouping talkers based on socio-indexical group information to guide speech recognition. variables can help—can be predicted by the particular structure of variability in cue distributions.

We know that listeners do, in fact, take advantage of structure in talker variability to guide speech perception. Perception of vowels (and fricatives) is affected by the perceived gender of the 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). Listeners’ perception of vowels also depends on other social variables: 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 More broadly, listeners are better at comprehending speech in noise from familiar talkers than from novel talkers (Nygaard and Pisoni 1998).

These findings establish that listeners use 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) grouping variables (including talker identity) to inform speech perception, but they don’t tell us exactly how useful these variables are. That is, what would be the consequences of ignoring these variables? How much do these consequences depend on the particular cues, category, or socio-indexical variable?

Our second study addresses this question, using the ideal adapter’s link between cue distributions and phonetic categorization. This requires data where the same talkers produce enough tokens for each relevant category in order to estimate the underlying distributions. This places substantial constraints on which datasets we can use, since most either do not contain enough tokens per talker, or (especially for stop voicing) only contain tokens from a subset of categories (e.g., only voiceless stops).



Question 3: How well could listeners *infer* socio-indexical variables given cue distributions?



((still not quite sure about this. needs to be punched up especially since it’s one of the main focuses of the special issue))

Finally, there is evidence we know 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) determine, on the basis of speech

²For the current study, we restrict ourselves to English, and focus primarily (but not exclusively) on *American* English.

alone, socio-indexical variables for a talker. 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

We include a talker’s *identity* as a socio-indexical variable (in the sense of what individual person they are). There is evidence that listeners can infer *talker identity* a talker’s 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

Again, what we don’t know is the particular information listeners are using to make these inferences, and at an even more basic level, how much information is available to them from *phonetic* cues (for a review, see Thomas 2002). Thus our final study aims to shed light on how much listeners can infer about a talker’s socio-indexical properties based on phonetic cue distributions alone. ~~This places further constraints on the data that we can use, because it requires that we have enough tokens, from enough talkers, who are annotated for socio-indexical variables~~



Datasets

~~Finally,~~ by connecting sociolinguistic and psycholinguistic perspectives on variability in speech perception, this work has broader implications. The ideal adapter framework has the potential to generate novel, testable predictions about how listeners learn and take advantage of structure in how talkers vary. In order to generate and test these predictions, we need to know, quantitatively, the relationship between socio-indexical variables, linguistic variables, and cue distributions. Thus the current work opens the door to new lines of empirical work on speech perception.

We analyze speech from two corpora, one focusing on vowels and the other on stop consonant voicing.

General methods

We next describe the datasets we use and the motivations for selecting these datasets. Then, we introduce our general modeling approach. The specific methods by which we quantify informativity, utility, and inferrability of socio-indexical grouping variables are discussed in their respective studies.

Data

Guided by our goals and their associated constraints, we selected two datasets. The first is a collection of vowel formants from the Nationwide Speech Project (NSP; Clopper, Pisoni, and Jong 2005), and the second a collection of voice onset times (VOT) for word-initial voiced and voiceless stops from the Buckeye corpus (Pitt et al. 2007, extracted by Wedel, *in prep*). Based on the variable annotated in the available data, we consider cue distributions conditioned on the following socio-indexical grouping variables:

- **Marginal:** is a control grouping, which includes all tokens from all talkers. This serves as a baseline against which more specific group distributions can be compared, and as a lower bound for speech recognition accuracy.
- **Sex:** this is coded as male/female for both vowels and stop voicing, allowing us to compare the role of sex for two different contrasts.
- **Age:** this is only relevant for VOT, because the talkers in the NSP are uniformly young. In the Buckeye corpus, age is coded as a binary variable (younger/older than 40, VOT only).
- **Dialect:** the NSP contains data from talkers from six dialect regions (see below for details).

- **Dialect+Sex:** Clopper, Pisoni, and Jong (2005) found that sex modulates dialect differences, so we also examine cue distributions conditioned on dialect and sex together (12 levels, vowels only).
- **Talker:** we also consider cue distributions conditioned on talker identity, as an upper bound on informativity and utility.

These socio-indexical variables that we focus on are generally *stable* over time for a single talker. This is a choice 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 and not necessarily static within a single individual (either producer or perceiver) (Goukles and Hay 2015; Levon 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.

Vowels

For vowels, we used data from the Nationwide Speech Project (Clopper, Pisoni, and Jong 2005). Specifically, we analyzed first and second formant frequencies (F1x F2, 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”ey), for a total of 2659 observations.

Because much of the variability in talkers is due to overall differences in formant frequencies, 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).

The major 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 dataset particular VOT corpus is that it contains observations of both voiced and voiceless stops, which from the same talkers. This allows us to assess the utility of socio-indexical grouping factors for recognizing directly assess how much talker variability in VOT distributions (Allen, Miller, and DeSteno 2003) actually impacts recognition

of voiced vs. voiceless stops. However, it , 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 ight increase in the overall informativity of talker identity, compared to the monolingual talkers alone.

Modeling approach

Each phonetic category was All of our analyses depend on knowing the *distribution* of cues for each phonetic category, at different levels of socio-indexical grouping. We obtain estimates of these distributions in the following way. ~~First~~, we assume that each phonetic category can be modeled as a normal distribution : over cue values (stop voicing as univariate distributions of over VOT, and vowels as bivariate distributions of F1 and F2. We used the maximum likelihood estimators for the model parameters, which are). These distributions are parametrized by their mean and their covariance matrix (or, equivalently, variance in the case of VOT). ~~Second~~, we fit these parameters to data from our corpora via maximum likelihood, using the sample mean and covariance matrix.

For each socio-indexical grouping level, we trained separate models for each phonetic category of tokens from each category. We do this separately for each group. For example, for gender, we obtain one estimate of the *ae* distribution based on all the tokens from male talkers, and one from all tokens from female talkers. Likewise, for dialect, we estimate one distribution based on all tokens from that category and grouping level (holding out test data when necessary, see below). The grouping levels we considered were talkers from the North dialect region, another one from tokens from Mid-Atlantic talkers, and so on.

Marginal (all tokens) Sex (male) Assuming that each category is a normal distribution is not a critical part of our approach, but rather a standard and convenient assumption. In particular, the normal distribution has a small number of parameters and this allows us to efficiently estimate the distribution for each category with a limited amount of data (e.g., five tokens per talker-level vowel distribution).

Study 1: Informativity of socio-indexical groupings about cue distributions

Our first goal is to assess how *informative* socio-indexical variables are about the cue distributions for each phonetic category, across levels of socio-indexical grouping and phonetic categories/female) Age (younger/older than 40, VOT only) Dialect (six regions, vowels only) Dialect+Sex (12 levels, vowels only) Talker cues.

Comparing cue distributions

Methods

In order to evaluate the One way to quantify how informative a socio-indexical grouping variable is about cue distributions is by comparing the group-level cue distributions with the *marginal* distribution of cues from all groups. The reason for this is that if a socio-indexical grouping variable (e.g., sex) is *not* informative about cue distributions, then the cue distributions for each group (e.g., male and female talkers) will be essentially identical, and hence indistinguishable from the *informativity overall* of cue distribution. If, on the other hand, a socio-indexical variables with respect to cue distributions themselves, we use variable *is*



informative about cue distributions, then the distribution for each group will deviate substantially from other groups, and by extension from the overall distribution as well. The particular measure we use to compare distributions is the Kullback-Leibler (KL) divergence to measure how much the group-specific cue distributions differ from the overall (marginal) cue distributions. This, which we now explain in detail.

Technical details

KL divergence (or relative entropy) is an information-theoretic comparison of two distributions (MacKay 2003, 34). 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. We do this separately for each linguistic category and group, and then average the results, calculating bootstrapped confidence intervals over groups (MacKay 2003, 98).

The In general, the KL divergence of Q from P is $DL(Q||P) = \int p(x) \log \frac{p(x)}{q(x)} dx$


$$DL(Q||P) = \int p(x) \log \frac{p(x)}{q(x)} dx \quad (1.1)$$

(with density functions q and p respectively). Intuitively, we can think of the KL divergence as how much better data—drawn from the distribution P —is explained by a “true” distribution P itself, compared to another distribution Q . This measure is always greater than zero, and equal zero only when $P = Q$ (MacKay 2003, 34).

In our case, $P = \mathcal{N}_G$ is a multivariate² normal cue distribution for the conditioned on a socio-indexical group, with mean μ_G and covariance Σ_G , while $Q = \mathcal{N}_M$ is the marginal multivariate normal (not conditioned on group) cue distribution with mean μ_M and covariance Σ_M . With some simplification³,³ the KL divergence of the marginal from the group distribution works out to be

$$DL(\mathcal{N}_M||\mathcal{N}_G) = \frac{1}{2} \left(\text{tr}(\Sigma_M^{-1}\Sigma_G) + (\mu_M - \mu_G)\Sigma_M^{-1}(\mu_M - \mu_G) - d + \log \frac{|\Sigma_M|}{|\Sigma_G|} \right) \quad (1.2)$$

where d is the dimensionality of the distribution, and logs are natural logarithms (log is the natural logarithm. For ease of interpretation, we report KL divergence in bits, which is the above quantity divided by $\log(2)$ corresponds to using \log_2 in equation 1.1, or dividing equation 1.2 by $\log(2)$).

For each phonetic category, we calculate the KL divergence of each group's cue distribution from the marginal distribution of cues from all talkers.  then average these single-category scores for each group to calculate the overall divergence for that group. Finally, for each grouping level, we average the divergence across groups, and compute bootstrapped confidence intervals over groups for this mean.

Results

Figure 1.1 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, we find that talker identity is an order of magnitude more informative about vowel distributions than about VOT distributions. This is important because it uses a quantitative measure to confirm the qualitative finding from previous work that there is less talker variability in VOT than in formant frequencies (e.g., Allen, Miller, and DeSteno 2003; Lisker and Abramson 1964; vs. Peterson and Barney 1952; Hillenbrand et al. 1995). 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 1.2 shows, this means that,



²The math is the same for the univariate special case, as with VOT.

³See, for instance, , p. 13.

³See, for instance, http://stanford.edu/~jduchi/projects/general_notes.pdf, p. 13.

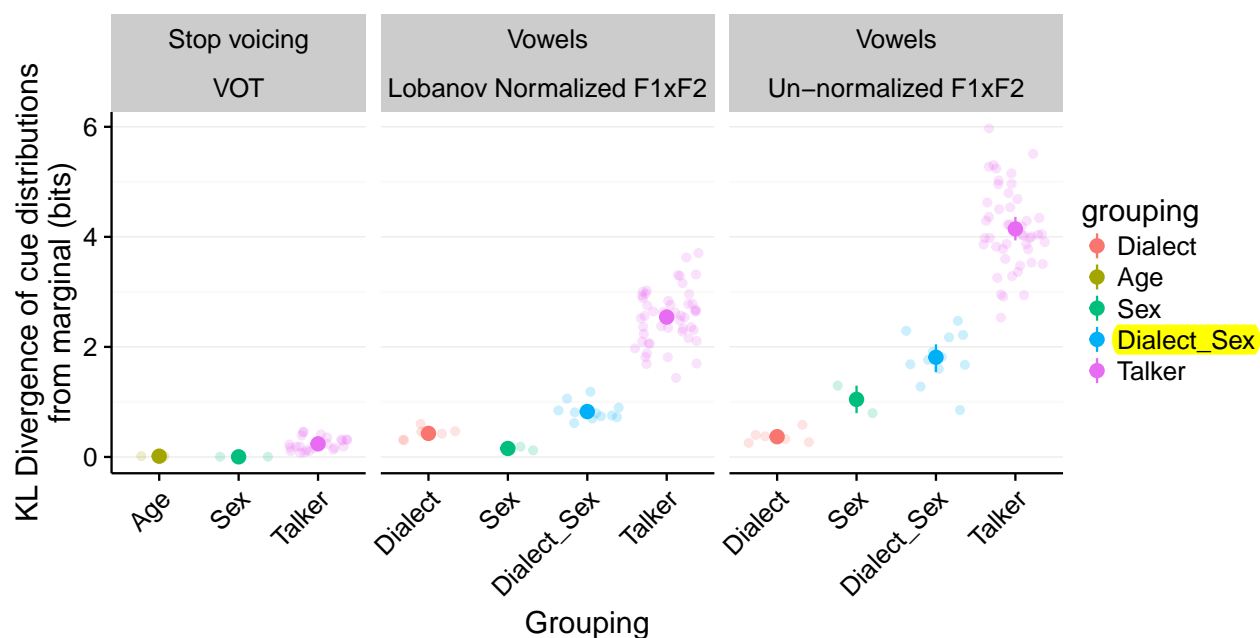


Figure 1.1: Socio-indexical variables are more informative about cue distributions for vowel (formants) than for stop voicing (vot). On top of this, more specific groupings (like **Talker** and **Dialect+Sex**) are more informative than broader groupings (Sex). This is indicated by higher KL divergence of each grouping level from marginal (showing mean and 95% bootstrapped CIs over groups).

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, on the whole, we find that more specific groupings are more informative than less specific groupings. This suggests that, within a group, talkers are more consistent than they are between groups. The exception to this pattern is that, for un-normalized formants, sex is more informative than dialect, even though dialect is more specific (8 talkers per dialect, vs. 24 per sex). The likely reason for this is that sex differences in physiology (e.g., vocal tract length) change formant frequencies for all vowels (Johnson 2006), but dialect variation is limited to certain dialect-vowel combinations (Clopper, Pisoni, and Jong 2005; Labov, Ash, and Boberg 2005).

As Figure 1.3 shows, 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).

Speech recognition

Next, to address the Figure 1.4 shows the KL divergence of each dialect's vowel distributions, demonstrating that dialects do indeed vary in how informative they are, both overall and by vowel. In particular, 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**

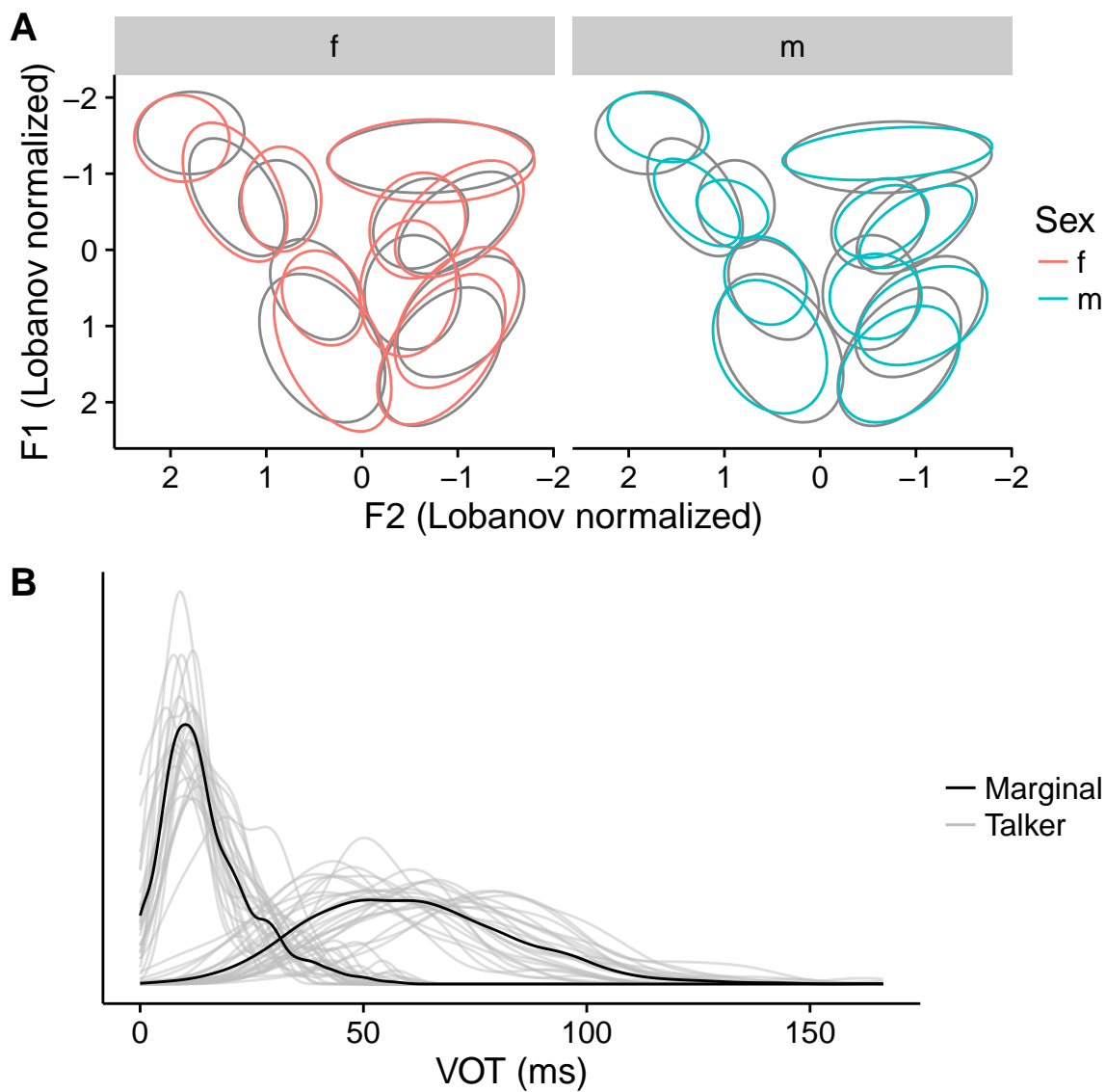


Figure 1.2: Male and female distributions of Normalized F1xF2 diverge from the marginal distributions (A) only slightly less than talker-specific VOT distributions diverge from marginal (B).

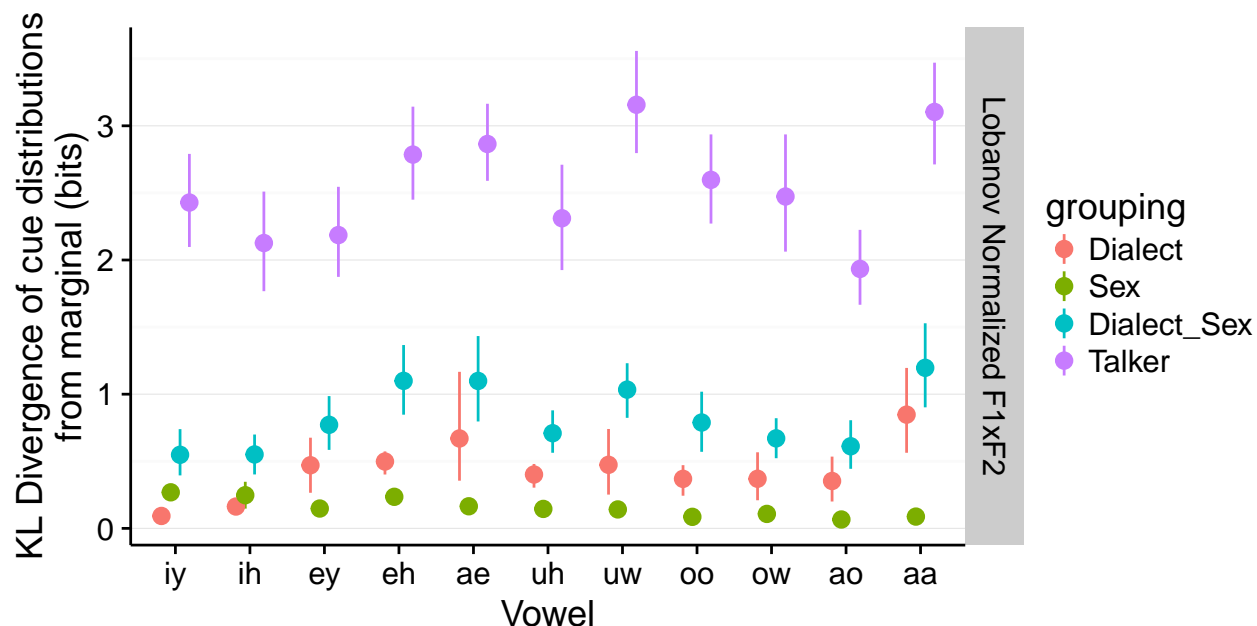


Figure 1.3: Individual vowels vary substantially in the informativity of grouping variables about their cue distributions. Only normalized F1xF2 is shown to emphasize dialect effects.

is, like the Northern **aa**, non-merged with **ao** (Clopper, Pisoni, and Jong 2005) and hence deviates from the marginal **aa** substantially.

Finally, these results show that, even after controlling for overall shifts in formant frequencies across all vowels via Lobanov normalization, there is still substantial talker variability. Normalization also substantially reduces the informativity of sex alone, which is to be expected given that most of the difference between male and female vowel distributions is due to the overall shifts in formant frequencies that Lobanov normalization removes. Interestingly, while normalization ~~also~~ reduces the informativity of dialect and sex considered together, their combination is ~~still~~ more informative than dialect alone. This ~~shows~~ that dialect differences themselves are modulated by sex.

Study 2: utility of socio-indexical groupings for speech recognition

Next, we evaluate the *utility* of **socio-indexical grouping** each grouping variable for speech recognition, **we calculate, for each level of** . By the utility of a socio-indexical grouping, **the probability of correct recognition** variable, we mean the benefit for speech perception from 1) tracking the cue distributions for phonetic categories *conditional* on group (e.g., for male and female talkers) and 2) knowing the value of that variable for a talker (e.g., whether a talker is male or female).

One way we ~~can~~ quantify ~~this benefit~~ is in terms of *probability of correct recognition* of phonetic categories. **We do this using an “ideal listener” model** (By treating speech perception as an inference problem, the ideal adapter (Kleinschmidt and Jaeger 2015; and the ideal listener models that it draws on, e.g. Clayards et al. 2008; Kleinschmidt and Jaeger 2015) that **compute the posterior probability of a category given an observed cue value based on the likelihood**) provides a link between group-specific cue distributions and the probability of correct recognition. We describe this link and how we actually calculate it, and then present the results for the datasets we consider here.

Methods

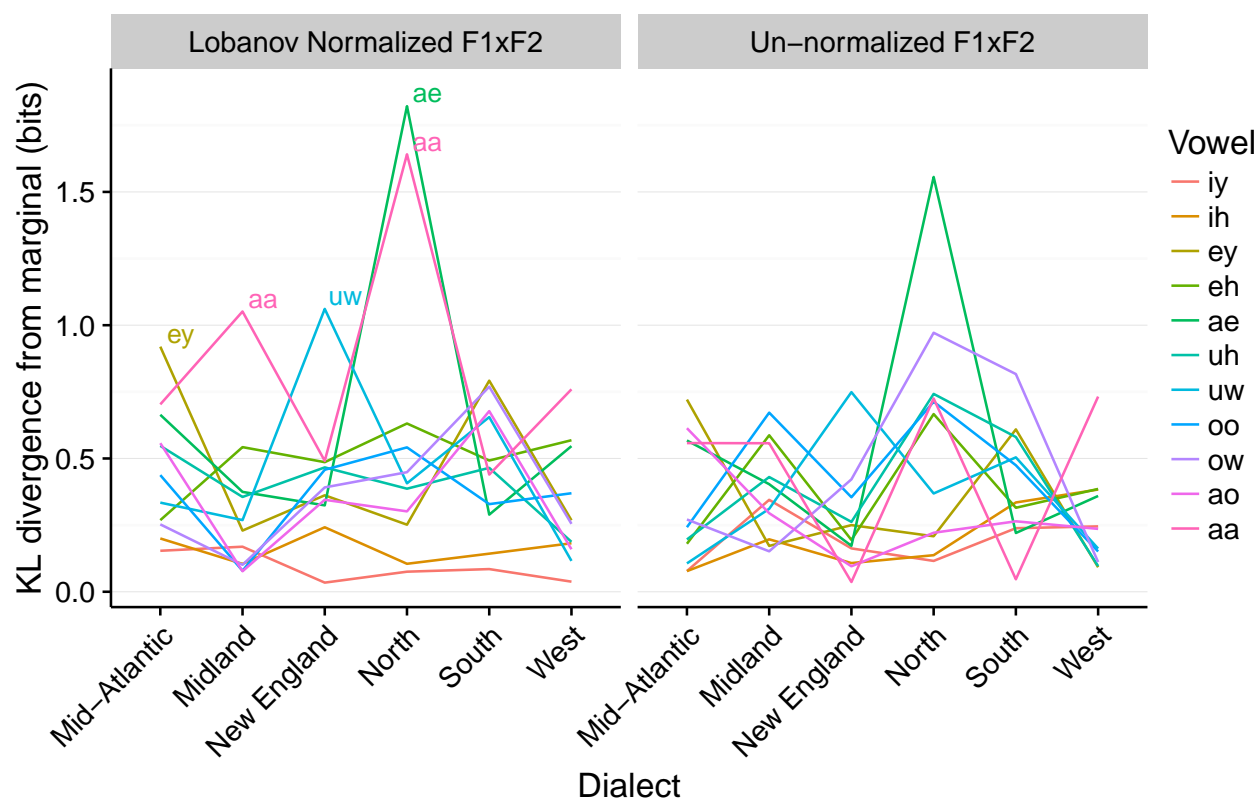



Figure 1.4: A small number of dialect/vowel combinations account for most of the divergence of dialect-specific vowel formant distributions. In particular, the distribution of *ae* and *aa* produced by Northern talkers diverge markedly more than any other vowel/dialect combination.

In the ideal adapter/listener, the link between cue distributions and recognition of phonetic categories is provided by Bayes Rule. Bayes Rule says that the *posterior probability* that a particular cue value came from a category is the *likelihood* of that cue value being generated by **each** that category's cue distribution, divided by the total likelihood of it being generated by any category.⁴ For instance, the posterior probability that a VOT of 20ms is a /b/ is the likelihood of a 20ms VOT under the /b/ VOT distribution, divided by the total likelihood of 20ms VOT under both /b/ and /p/. **By doing this**

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. Separating distributions based on a socio-indexical grouping variable can affect the overlap between different phonetic categories, and thus the rate of correct recognition is a measure of the *utility* of that 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 (that is, 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 **provides an estimate of**, **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.

We


Technical details

~~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 the sake of brevity, we do not present results when group is unknown.** 

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.

Indexical group recognition

Finally, to address 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 :

⁴~~Assuming~~ that the prior probability of each category is equal, ~~which we assume here for the sake of simplicity.~~

⁵ 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 .

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

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 $p(\text{sex}|x)$ To assess statistical significance, we bootstrap over talkers. This is a non-parametric approach that provides confidence intervals and $p(\text{dialect}|x)$ for each talker.

Controls and assessing significance

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 p values for effects at the population level, ~~given 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.⁶ For testing group differences, we use the proportion of resampled datasets with same-sign difference as the bootstrapped p value. , ~~without assuming a particular noise distribution.~~



Cross-validation

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** , **training** 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.

Different group sizes

Avoiding biases from diffent 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 2.2.2). **This bias would make it impossible to meaningfully compare probability of correct recognition *across* grouping levels, defeating the purpose of this analysis.**

⁶While 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.

To correct for this, **after holding out the test talker**, we randomly subsampled **three** talkers (without replacement) within each group in the training set **to be the same (that is, after holding out the test talker)**. This ensures that every group has is the same size as the smallest group (**3 talkers, based on across grouping levels**). For the studies reported here, that corresponds to the test talker’s Dialect+Sex group.⁶).

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.

Results

Informativity of socio-indexical groupings about cue distributions

We first analyze how informative each **This is not necessary for the VOT data: the Buckeye Corpus is balanced by age and sex, the two 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. **variables we consider**.

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).

Results

Figure 1.1 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 1.2 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).

Figure 1.5 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 : knowing whether a talker is male vs. female (or young vs. old) provides no advantage when classifying their VOTs as voiced or voiceless**. This is consistent with the finding above that VOT distributions **themselves** 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 across groups. Even using a talker’s own distributions provides only a minimal advantage (on the order of 2% increase in accuracy , over marginal,

⁶We 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.

Male and female distributions of Normalized F1xF2 diverge from the marginal distributions (A) only slightly less than talker-specific VOT distributions diverge from marginal (B).

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 1.3, 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). 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 1.4 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.

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.

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).

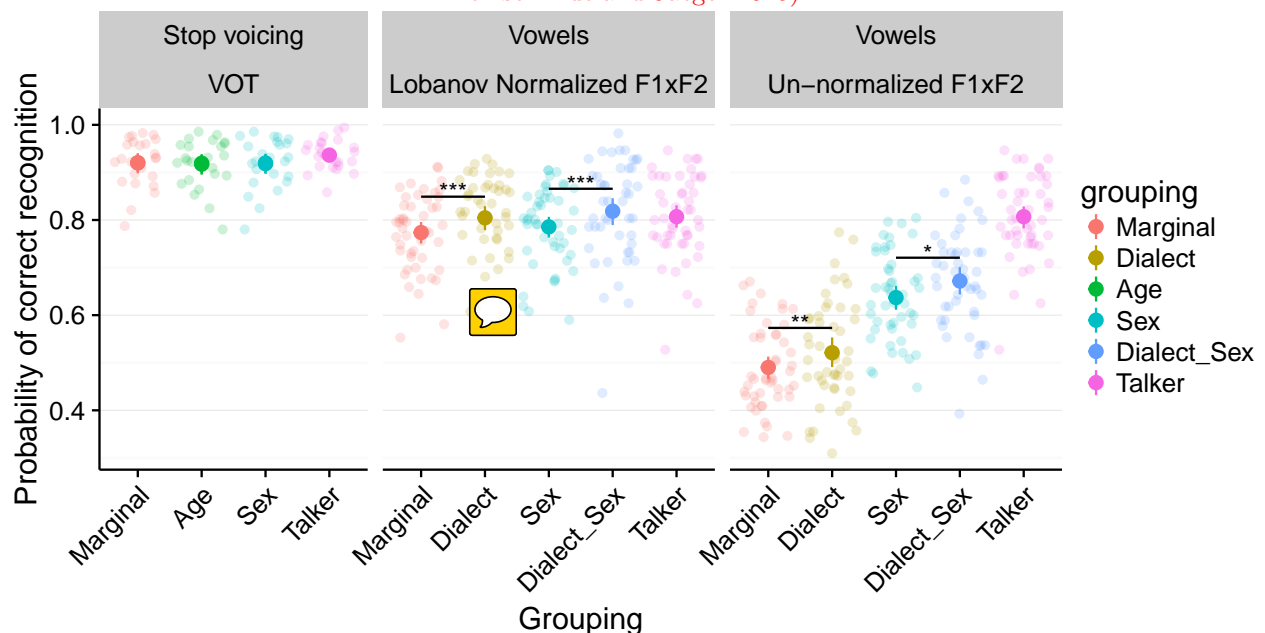


Figure 1.5: Speech recognition accuracy using for marginal, group-level, and talker-specific cue distributions. Small points show individual talkers, and large points and lines show mean and bootstrapped 95% CIs over talkers. Marginal and group-level accuracy is based on leave-one-talker out cross-validation, 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 *** $p < 0.001$.

age-, and sex-conditioned distributions, all three $p < 0.01$). These comparisons are also significant when using log-odds of correct recognition, rather than raw probabilities.⁷

Normalized For vowels, 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).

Also paralleling the cue distributions themselves, classifying according to sex-specific distributions provides Conditioning vowel cue distribution on sex—either alone, relative to marginal, or in addition to dialect—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 $p < 0.05$).

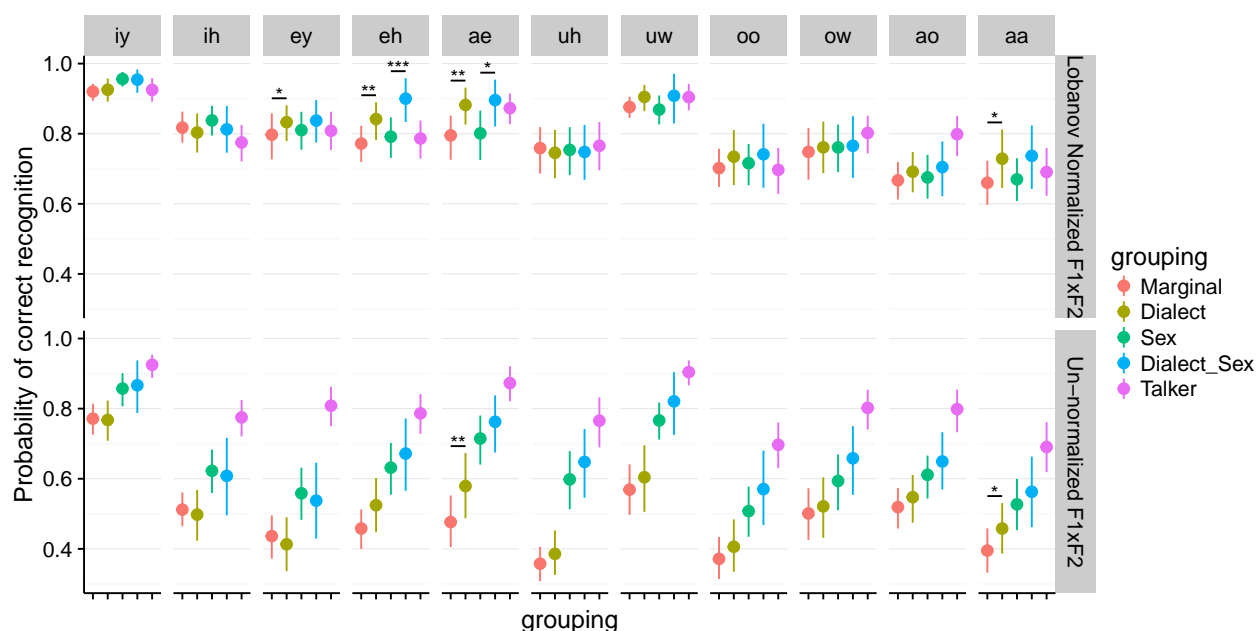


Figure 1.6: Probability of correct recognition varies across vowels, overall and according to the socio-indexical grouping variable. Bars and stars show significant improvement from conditioning on dialect, above marginal or in addition to sex alone.

The utility of socio-indexical grouping for recognizing individual vowels largely mirrors the overall pattern (Figure 1.6). The exception is that As with informativity, 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 1.7). 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 1.4). Most notably, conditioning on dialect provides a consistent advantage for talkers from the North dialect region, on the order of 10%.

⁷These comparisons are also significant when using log-odds of correct recognition, rather than raw probabilities.

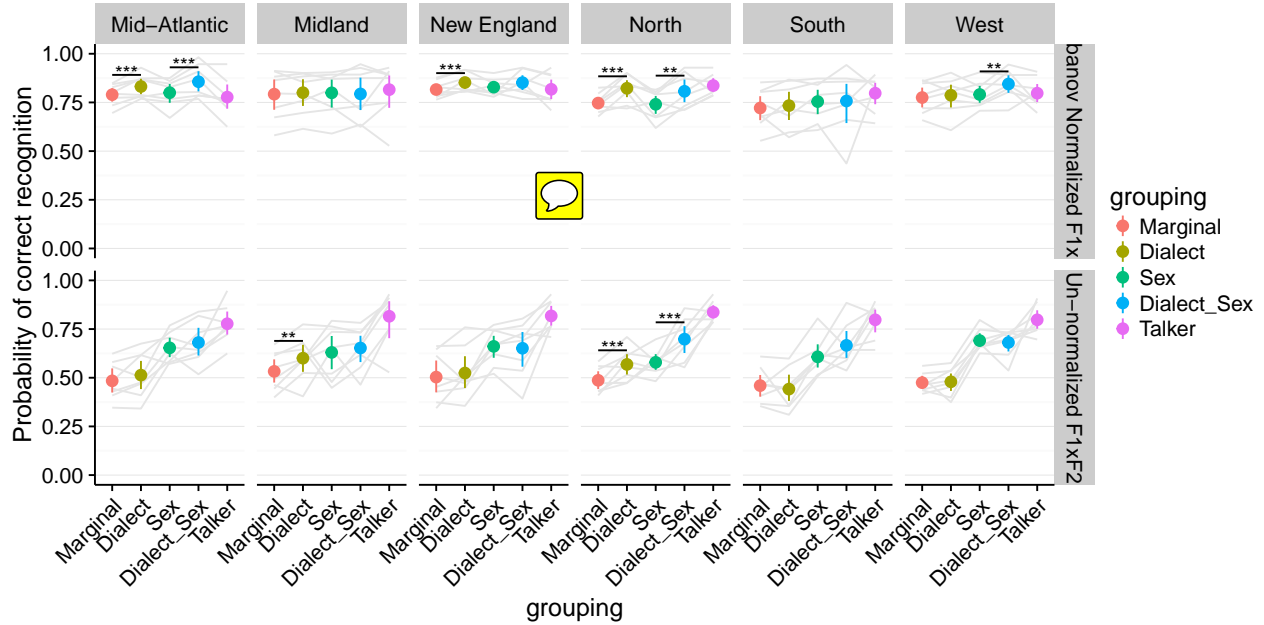


Figure 1.7: The utility of socio-indexical variables varies across dialects. Dialect itself is particularly informative only for talkers from the Mid-Atlantic and North regions. Each line shows a single talker, to emphasize within-talker changes in accuracy with grouping level, and large points and confidence intervals show mean accuracy and bootstrapped 95% CIs over talkers.

Inferring socio-indexical variables from cue distributions

Study 3: Inferring socio-indexical variables from cue distributions

Finally, we assess how well listeners **could infer** would be able to determine values of socio-indexical variables **from unlabeled acoustic-phonetic cues**, based on cue distributions alone. Qualitatively, a listener should be able to determine a talker’s socio-indexical group based on phonetic cues to the extent that the distributions of those cues differ across groups. Here we quantify this using the same computational tools that we used to quantify the utility of socio-indexical grouping for speech perception. Specifically, we ask how well a listener could *infer* a talker’s group, based on the **group-conditional cue distributions**. **We measure this by the accuracy with which an “ideal listener” can categorize a distributions of cues produced by other talkers in the same and different groups.**

Methods

The process of inferring socio-indexical group parallels the process of inferring phonetic categories: the posterior probability that a talker belongs to a particular group is proportional to the likelihood of the cues they produce under that group’s cue distributions, relative to the total likelihood under all groups’ distributions.

We formalize this with the same kind of ideal observer model used for phonetic recognition. That is, we compute the posterior probability of each socio-indexical group $g = j$, given all of the talker’s **group membership** for each 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* likelihood of observing a cue value x_i under group g , we first have to marginalize over categories v_i :

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

We perform this analysis separately for each level of **socio-indexical grouping variable**. For instance, for each talker we compute both $p(\text{sex}|x)$ and $p(\text{dialect}|x)$.

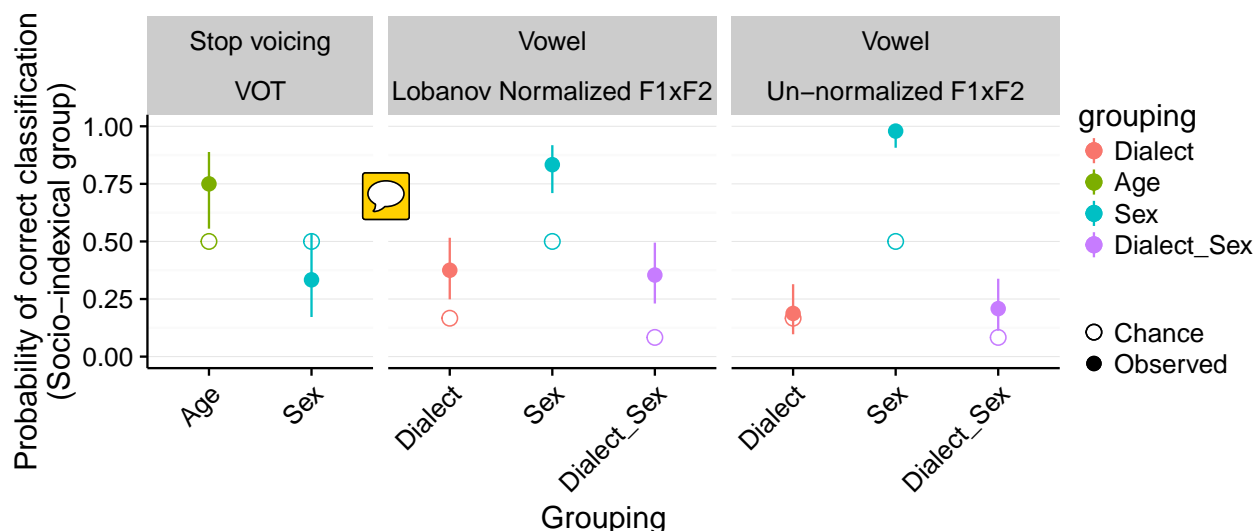


Figure 1.8: Probability of correctly classifying a talker's socio-indexical group varies with the grouping variable, contrast, and cues. A talker is correctly classified if the overall posterior probability of their actual group given their unlabeled productions is the highest of all groups.

Results

For **most** groupings, it is possible to infer each talker's group with above chance accuracy, given only that talker's unlabeled observed cues (Figure 1.8; all $p < 0.01$, except for inferring a talker's sex based on their VOT distributions, and dialect from un-normalized F1xF2 distributions, both $p > 0.15$). **Surprisingly, despite the fact that VOT distributions do not differ markedly by age, it is still possible to infer a talker's age based on VOT with above chance accuracy (75%, 95% CI 58–92%, $p < 0.01$).**

In some respects, these results mirror the patterns of informativity about the cue distributions themselves (Figure 1.1). 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 VOT⁸ (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.

⁸Barring, of course, the possibility that VOT is systematically affected by neighboring vowels, and hence informative about them.

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 1.1 and 1.5.

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,~~ 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 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  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 listener’s 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 2015 ). 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.⁹ 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

⁹Even 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.

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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