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Unravelling the time-course of listener adaptation to an unfamiliar talker

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Author Note

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10 Abstract

- 11 We investigate constraints on adaptive speech perception during the initial encounters with
- 12 unfamiliar speech patterns. Such adaptive changes are now considered important to spoken
- 13 language understanding, overcoming substantial cross-talker variability in the realization of
- speech categories. We present evidence from a novel incremental exposure-test paradigm to assess
- 15 how previously experienced cross-talker variability guides (and thus constrains) listeners'
- adaptation. Specifically, we ask adaptation is constrained weakly—slower and sublinear, but
- 17 continued adaptation with increasing exposure—or strongly—adaptation only up to a point, after
- which additional exposure has no benefits (at least not prior to, e.g., sleep). The results
- contribute to a proposed theoretical distinction between two hypotheses about the mechanisms
- 20 underlying the intial moments of adaptation, model learning vs. model selection.
- 21 Keywords: speech perception; adaptation; incremental changes; distributional learning
- 22 Word count: X

Unravelling the time-course of listener adaptation to an unfamiliar talker

24 1 TO-DO

25 1.1 Highest priority

- MARYANN
- Figure out why slopes aren't identical across conditions under our current way of averaging exposure across all participants.
- fit nested model: Condition / (block*VOT). Sample prior = "yes". This is to make the argument of block-to-block change within each condition.
- make a hypothesis table that summarises the main effect of block for each exposure condition
- Non-parametric density plot.
- Apply correction for vowel duration!
- Try an add line to table 2 to separate the unlearning hypothesis from the others (low priority). Add +40 vs baseline sub-heading

37 1.2 Medium priority

- MARYANN
- Fix a lot of the outstanding XXXes. Fill in the references in library.bib
- Heterogenous normal distribution
- FLORIAN

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- think about table 1 and 2: how to change the wording on tables to actually refer to
 intercepts rather than PSEs or change the figures? Changing current representations of
 analyses to improve intuitive-ity.
 - write overview of results

- restructure results presentation.
- write SI sections with proofs

48 1.2.1 Lower Priority

- MARYANN
- Decide on PSE vs. category boundary
- standardize BE vs. AE spelling (categoriz/sation, label(l)ed, synthesiz/sed etc.)
- Figure 2: A small figure to anticipate the type of format in the main figure. Exposure is

 x-axis (less to more exposure). Under one prediction you keep growing 00 prediction o BBU

 model. The other one is plataeuing and converging against something.
- Florian
- compare IBBU predictions over blocks with human behavioural data

57 1.3 To do later

• Everyone: Eat ice-cream and perhaps have a beer.

59 1 Introduction

One of the hallmarks of human speech perception is its adaptivity. Listeners' interpretation of acoustic input can change within minutes of exposure to an unfamiliar talker, supporting robust 61 speech recognition across talkers (Bradlow & Bent, 2008; Clarke & Garrett, 2004; Xie, Liu, & 62 Jaeger, 2021; Xie, Weatherholtz, et al., 2018). Recent reviews have identified distributional learning of marginal cue statistics ('normalization,' Apfelbaum & McMurray, 2015; McMurray & Jongman, 2011) or the statistics of cue-to-category mappings as an important mechanism affording this adaptivity ('representational learning,' Clayards, Tanenhaus, Aslin, & Jacobs, 2008; Davis & Sohoglu, 2020; Idemaru & Holt, 2011; Kleinschmidt & Jaeger, 2015; for review, Schertz & Clare, 2020; Xie, Jaeger, & Kurumada, 2023). This hypothesis has gained considerable influence over the past decade, with findings that changes in listener perception are qualitatively predicted by the statistics of exposure stimuli (Bejjanki, Beck, Lu, & Pouget, 2011; Clayards et al., 2008; Idemaru & Holt, 2020; Kleinschmidt & Jaeger, 2012; Nixon, Rij, Mok, Baayen, & Chen, 71 2016; Tan, Xie, & Jaeger, 2021; Theodore & Monto, 2019; munson2011-thesis?; for important caveats, see harmon2018?). We investigate an important constraint on this type of adaptivity that is suggested by 74 recent findings. Kleinschmidt and Jaeger (2016) exposed L1-US English listeners to recordings of 75 /b/-/p/ minimal pair words like beach and peach that were acoustically manipulated. Separate 76 groups of listeners were exposed to distributions of voice onset times (VOTs)—the primary cue distinguishing words like beach and peach—that were shifted by up to +30 ms, relative to what one might expect from a 'typical' talker (Figure 1A). In line with the distributional learning hypothesis, listeners' category boundary or point of subjective equality (PSE)—i.e., the VOT for which listeners are equally likely to respond "b" or "p"—shifted in the same direction as the exposure distribution (Figure 1B). Also in line with the distributional learning hypothesis, these 82 shifts were larger the further the exposure distributions were shifted. However, Kleinschmidt and 83 Jaeger also observed a previously undocumented property of these adaptive changes: shifts in the exposure distribution had less than proportional (sublinear) effect on shifts in PSE (Figure 1C). 85 While this finding is broadly compatible with the hypothesis of distributional learning, it points

to important not well-understood constraints on adaptive speech perception.

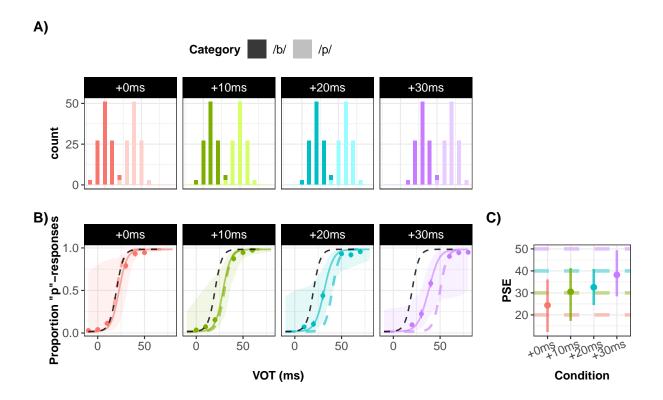


Figure 1. Design and results of Kleinschmidt and Jaeger (2016) replotted. **Panel A:** Different groups of participants were exposed to different shifts in the mean VOT of /b/ and /p/. **Panel B:** Categorisation functions of individual participants depending on the exposure condition (shift in VOT means of /b/ and /p/). For reference, the black dashed line shows the categorisation function of the 0-shift condition. The colored dashed lines shows the categorisation function expected for an ideal observer that has fully learned the exposure distributions. **Panel C:** Mean and 95% CI of participants' points of subjective equality (PSEs), relative to the PSE of the ideal observers.

For example, influential models of adaptive speech perception predict proportional, rather 88 than sublinear, shifts (for proof, see SI??). This is the case both for incremental Bayesian 89 belief-updating model (Kleinschmidt & Jaeger, 2011) and general purpose normalization accounts 90 (McMurray & Jongman, 2011)—models that have been found to explain listeners' behavior well in experiments with less substantial changes in exposure. There are, however, proposals that can 92 accommodate this finding. Some proposals distinguish between two types of mechanisms that 93 might underlie representational changes, model learning and model selection (Xie, Weatherholtz, et al., 2018, p. 229). The former refers to the learning of a new category representations—for 95 example, learning a new generative model for the talker (Kleinschmidt & Jaeger, 2015, pt. II) or 96 storage of new talker-specific exemplars (Johnson, 1997; Sumner, 2011). Xie and colleagues

hypothesized that this process might be much slower than is often assumed in the literature, potentially requiring multiple days of exposure and memory consolidation during sleep (see also Fenn & Hambrick, 2013; Tamminen, Davis, Merkx, & Rastle, 2012; Xie, Earle, & Myers, 2018). 100 Rapid adaptation that occurs within minutes of exposure might instead be achieved by selecting 101 between existing talker-specific representations that were learned from previous speech 102 input—e.g., previously learned talker-specific generative models (see mixture model in 103 Kleinschmidt & Jaeger, 2015, pp. 180–181) or previously stored exemplars from other talkers 104 (Johnson, 1997). Model learning and model selection both offer explanations for the sublinear 105 effects observed in Kleinschmidt and Jaeger (2016). But they suggest different predictions for the 106 evolution of this effect over the course of exposure. 107

Under the hypothesis of model learning, sublinear shifts in PSEs can be explained by 108 assuming a hierarchical prior over talker-specific generative models $(p(\Theta))$ in Kleinschmidt & 109 Jaeger, 2015, p. 180). This prior would 'shrink' adaptation towards listeners' priors—similar to 110 the effect of random by-subject or by-item effects in generalized linear mixed-effect models, which 111 shrink group-level effect estimates towards the population mean of the data (Baayen, Davidson, & 112 Bates, 2008). Critically, as long as these priors attribute non-zero probability to even extreme 113 shifts (e.g., the type of Gaussian prior used in mixed-effects models), this predicts listeners' PSEs 114 will continue to change with increasing exposure until they have converged against the PSE that 115 is ideal for the exposure statistics. In contrast, the hypothesis of model selection predicts that 116 rapid adaptation is more strictly constrained by previous experience: listeners can only adapt 117 their categorisation functions up to a point that corresponds to (a mixture of) previously learned 118 talker-specific generative models. This would imply that at least the earliest moments of adaptation are subject to a hard limit (Figure 2): exposure helps listeners to adapt their 120 interpretation to more closely aligned with the statistics of the input, but only to a certain point. 121

The present study employs a novel incremental exposure-test paradigm to address two questions. We test whether the sublinear effects of exposure observed in recent work replicate for exposure that (somewhat) more closely resembles the type of speech input listeners receive on a daily basis. And, we evaluate the predictions of the model learning and selection hypotheses against human perception. We take this question to be of interest beyond the specific hypotheses

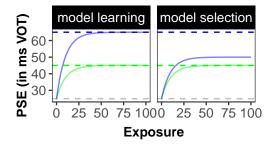


Figure 2. Contrasting predictions of model learning and model selection hypotheses about the incremental effects of exposure on listeners' categorisation function. Both hypothesis predict incremental adaptation towards the statistics of the input, as well as constraints on this adaptation. The two hypotheses differ, however, in that model selection predicts a hard limit on how far listeners' can adapt during initial encounters with an unfamiliar talker.

we contrast: whether there are hard limits to the benefits of exposure to unfamiliar speech patterns ultimately has consequences for education and medical treatment.

All data and code for this article can be downloaded from https://osf.io/hxcy4/. The article is written in R markdown, allowing readers to replicate our analyses with the press of a button using freely available software (R, R Core Team, 2022; RStudio Team, 2020), while changing any of the parameters of our models (see SI, ??).

2 Experiment

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We revise the standard paradigm used to investigate distributional learning in speech perception. 134 Previous work has employed 'batch testing' designs, in which changes in categorisation responses 135 are assessed only after extended exposure to hundreds of trials or by averaging over extended 136 exposure (e.g., Clayards et al., 2008; Idemaru & Holt, 2011, 2020; Kleinschmidt & Jaeger, 2016; 137 Nixon et al., 2016; Theodore & Monto, 2019; harmon2018?; munson2011?). These designs are 138 well-suited to investigate cumulative effects of exposure but are less so to identify constraints on 139 rapidly unfolding incremental adaptation. To be able to detect both incremental and cumulative 140 effects of exposure, within and across exposure conditions, we employed the repeated 141 exposure-test design shown in Figure 3. 142

The use of test blocks that repeat the same stimuli across blocks and exposure conditions deviates from previous work (Clayards et al., 2008; Kleinschmidt & Jaeger, 2016; Theodore &

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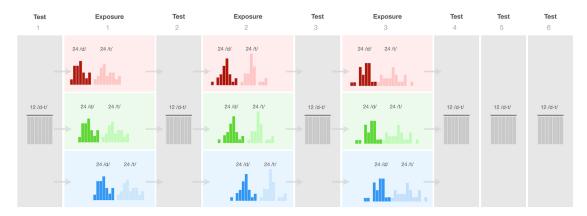


Figure 3. Exposure-test design of the experiment. Test blocks presented identical stimuli within and across conditions

Monto, 2019). This design feature allowed us to assess how increasing exposure affects listeners' perception without making strong assumptions about the nature of these changes (e.g., linear 146 changes across trials). We kept test blocks short for two reasons. First, previous work has found 147 that repeated testing over uniform test continua can reduce or undo the effects of informative 148 exposure (Cummings & Theodore, 2023; Liu & Jaeger, 2018, 2019). Second, since we held test 149 stimuli constant across exposure conditions, the distribution—and thus the relative 150 unexpectedness—of test stimuli differed to different degrees from the three exposure distributions. 151 By keeping tests short relative exposure (12 vs. 48 trials), we aimed to minimize the influence of 152 test trials on adaptation. The final three test blocks were intended to ameliorate the potential 153 risks of this novel design: in case adaptation remains stable despite repeated testing, those 154 additional test blocks were meant to provide additional statistical power to detect the effects of 155 cumulative exposure. 156

We also adjusted the standard distributional learning paradigm to increase the ecological validity of the exposure and test stimuli. The pioneering works that inspired the present study employed speech stimuli that did not exhibit the natural correlations between different acoustic-phonetic cues that characterise human speech, and that were clearly identifiable as robotic speech (Clayards et al., 2008; Kleinschmidt & Jaeger, 2016). These studies also followed the majority of research on distributional learning in language (e.g., Maye, Werker, & Gerken, 2002; Pajak & Levy, 2012) and designed rather than sampled the exposure distributions. As a consequence, exposure distributions in these experiments tend to be symmetrically balanced

around the category means—unlike in everyday speech input. Indeed, all of the works we follow
here further used categories with *identical* variances (e.g., identical variance along VOT for /b/
and /p/, Clayards et al., 2008; Kleinschmidt & Jaeger, 2016; or /g/ and /k/, Theodore & Monto,
2019). This, too, is highly atypical for everyday speech input (Chodroff & Wilson, 2018; Lisker &
Abramson, 1964). The present study takes several modest steps to ameliorate these issues.

2.1 Methods

171 2.1.1 Participants

We recruited 126 participants from the Prolific crowdsourcing platform. We used Prolific's 172 pre-screening to limit the experiment to participants (1) of US nationality, (2) who reported to be 173 English speaking monolinguals, and (3) had not previously participated in any experiment from 174 our lab on Prolific. Prior to the start of the experiment, participants had to confirm that they (4) 175 had spent the first 10 years of their life in the US, (5) were in a quiet place and free from 176 distractions, and (6) were in-ear or over-the-ears headphones that cost at least \$15. An additional 177 115 participants loaded the experiment but did not start or complete it.¹ 178 Participants took an average of 31.6 minutes to complete the experiment (SD = 20179 minutes) and were remunerated \$8.00/hour. An optional post-experiment survey recorded 180 participant demographics using NIH prescribed categories, including participant sex (59 = female, 181 60 = male, 3 = NA), age (mean = NA years; 95% quantiles = 20-62.1 years), race (6 = Black, 31 182 = White, 85 = NA), and ethnicity (6 = Hispanic, 113 = Non-Hispanic, 3 = NA). 183 Participants' responses were collected via Javascript developed by the Human Language 184 Processing Lab at the University of Rochester (JSEXP?) and stored via Proliferate developed at, 185 and hosted by, the ALPs lab at Stanford University (Schuster, S, 2020). 186

¹ Unlike in lab-based experiments, for which participants' right to stop the experiment at any point is costly (both in terms of physical effort and perceived social cost), exercising this right in web-based experiments is essentially cost free—in particular, if exercised early in the experiment.

87 2.1.2 Materials

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We recorded 8 tokens each of four minimal word pairs (dill/till, dim/tim, din/tin, and dip/tip)
from a 23-year-old, female L1-US English talker from New Hampshire, judged to have a "general
American" accent. In addition to these critical minimal pairs we also recorded three words that
did not did not contain any stop consonant sounds ("flare", "share", and "rare"). These word
recordings were used for catch trials. Stimulus intensity was normalized to 70 dB sound pressure
level for all recordings.

The critical minimal pair recordings were used to create four VOT continua using a script 194 (Winn, 2020) in Praat (Boersma & Weenink, 2022). This approach resulted in continuum steps 195 that sound natural (unlike the highly robotic-sounding stimuli employed in Clayards et al., 2008; 196 Kleinschmidt & Jaeger, 2016). A post-experiment survey asked participants: "Did you notice 197 anything in particular about how the speaker pronounced the different words (e.g. till, dill, etc.)?" 198 No participant reported that the stimuli sounded unnatural. The procedure also maintained the 199 natural correlations between the most important cues to word-initial stop-voicing in L1-US 200 English (VOT, F0, and vowel duration). Specifically, the F0 at vowel onset of each stimulus was 201 set to respect the linear relation with VOT observed in the original recordings of the talker. The 202 duration of the vowel was set to follow the natural trade-off relation with VOT (Allen & Miller, 203 1999). Further details on the recording and resynthesis procedure are provided in the 204 supplementary information (SI, ??). 205

The VOTs generated for each continuum ranged from -100 to +130 ms in 5 ms steps.² A norming experiment (N = 24 participants) reported in the SI (??) was used to select the three minimal pair continua that elicited the most similar categorization responses (dill-till, din-tin, and dip-tip). These three continua were used to create the exposure conditions shown in Figure 3.

² We follow previous work (Kleinschmidt, 2020; Lisker & Abramson, 1964) and refer to pre-voicing as negative VOTs though we note that pre-voicing is perhaps better conceived of as a separate phonetic feature (for discussion, see **REF?**). Estimates of the proportion of voiced stops produced with pre-voicing in L1-US English vary substantially between studies (between 20% and 57%) (e.g. Lisker & Abramson, 1967; Smith, 1978; Westbury, 1979). Because pre-voicing is not regarded as a phonemic determinant of English, some studies either discard such data or ignore them altogether (e.g. Zue (1976); Klatt (1975); Chodroff and Wilson (2017)). In some studies that do report pre-voicing, the majority of the tokens were attributed to a minority of talkers (Flege & Brown Jr, 1982; e.g. Lisker & Abramson, 1967). Although speakers tend to prefer one type of production over the other they do not typically use one type exclusively (Docherty, 2011).

$\mathbf{2.1.3}$ Procedure

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At the start of the experiment, participants acknowledged that they met all requirements and 211 provided consent, as per the Research Subjects Review Board of the University of Rochester. 212 Participants also had to pass a headphone test (Woods, Siegel, Traer, & McDermott, 2017), and 213 were instructed to not change the volume throughout the experiment. Following instructions, 214 participants completed 234 two-alternative forced-choice categorisation trials (Figure 4). 215 Participants were instructed that they would hear a female talker say a single word on each trial, 216 and were asked to select which word they heard. Participants were asked to listen carefully and 217 answer as quickly and as accurately as possible. They were also alerted to the fact that the 218 recordings were subtly different and therefore may sound repetitive. 219

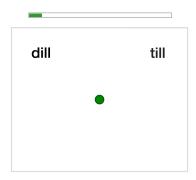


Figure 4. Example trial display. When the green button turned bright green, participants had to click on it to play the recording.

Unbeknownst to participants, the 234 trials were split into exposure (54 trials each) and test blocks (12 trials each). Participants were given the opportunity to take breaks after every 60 trials, which was always during an exposure block. Finally, participants completed an exit survey and an optional demographics survey.

Test blocks. The experiment started with a test block. Test blocks were identical within and across conditions, always including 12 minimal pair trials assessing participants' categorization at 12 different VOTs (-5, 5, 15, 25, 30, 35, 40, 45, 50, 55, 65, 70 ms). A uniform distribution over VOTs was chosen to maximize the statistical power to determine participants' categorisation function. The assignment of VOTs to minimal pair continua was randomized for each participant, while counter-balancing it within and across test blocks. Each minimal pair

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²³⁰ appear equally often within each test block (four times), and each minimal pair appear with each VOT equally often (twice) across all six test blocks (and no more than once per test block).

Each trial started with a dark-shaded green fixation dot being displayed. At 500ms from trial onset, two minimal pair words appeared on the screen, as shown in Figure 4. At 1000ms from trial onset, the fixation dot would turn bright green and participants had to click on the dot to play the recording. This was meant to reduce trial-to-trial correlations by resetting the mouse pointer to the center of the screen at the start of each trial. Participants responded by clicking on the word they heard and the next trial would begin.

Exposure blocks. Each exposure block consisted of 24 /d/ and 24 /t/ trials, as well as 6 catch trials that served as a check on participant attention throughout the experiment (2 instances for each of three combinations of the three catch recordings). With a total of 144 trials, exposure was substantially shorter than in similar previous experiments (cf. 228 trials in Clayards et al., 2008; 222 trials in Kleinschmidt, 2020; 2 x 236 trials, Theodore & Monto, 2019; 456 trials, Nixon et al., 2016).

The distribution of VOTs across the 48 /d/-/t/ trials depended on the exposure condition. 244 Specifically, we first created a baseline condition. Although not critical to the purpose of the 245 experiment, we aimed for the VOT distribution in this condition to closely resemble participants' 246 prior expectations for a 'typical' female talker of L1-US English (for details, see SI, ??). The mean and standard deviations for /d/ along VOT were set at 5 ms and 8.9 ms, respectively. The 248 mean and standard deviations for /t/ were set at 50 ms and 16 ms, respectively. To create more 249 realistic VOT distributions, we sampled from the intended VOT distribution (top row of Figure 250 5). This creates distributions that more closely resemble the type of distributional input listeners 251 experience in everyday speech perception, deviating from previous work, which exposed listeners 252 to highly unnatural fully symmetric samples (Clayards et al., 2008; Kleinschmidt, 2020; 253 Kleinschmidt & Jaeger, 2016). 254

Half of the /d/ and half of the /t/ trials were labeled, the other half was unlabeled
(paralleling one of the conditions in Kleinschmidt, Raizada, & Jaeger, 2015). Unlabeled trials
were identical to test trials except that the distribution of VOTs across those trials was bimodal

(rather than uniform), and determined by the exposure condition.³ Labeled trials instead
presented two response options with identical stop onsets (e.g., din and dill). This effectively
labeled the input as belonging to the intended category (e.g., /d/).

Next, we created the two additional exposure conditions by shifting these VOT
distributions by +10 or +40 ms (see Figure 5). This approach exposes participants to
heterogeneous approximations of normally distributed VOTs for /d/ and /t/ that varied across
blocks, while holding all aspects of the input constant across conditions except for the shift in
VOT. The order of trials was randomized within each block and participant, with the constraint
that no more than two catch trials would occur in a row. Participants were randomly assigned to
one of 3 (exposure condition) x 3 (block order) x 2 (placement of response options) lists.

268 2.1.4 Exclusions

Due to data transfer errors 4 participants' data were not stored and therefore excluded from 269 analysis. We further excluded from analysis participants who committed more than 3 errors out 270 of the 18 catch trials (<83% accuracy, N = 1), participants who committed more than 4 errors 271 out of the 72 labelled trials (<94% accuracy, N = 0), participants with an average reaction time 272 more than three standard deviations from the mean of the by-participant means (N = 0), 273 participants who had atypical categorisation functions at the start of the experiment (N = 2, see274 SI, ?? for details), and participants who reported not to have used headphones (N = 0). This left 275 for analysis 17,136 exposure and 8,568 test observations from 119 participants (94\% of total), 276 evenly split across the three exposure conditions.

278 **2.2** Results

We analyzed participants' categorisation responses during exposure and test blocks in two
separate Bayesian mixed-effects psychometric models, using brms (Bürkner, 2017) in R (R Core

³ Previous studies have estimated changes in participants' categorisation responses by analyzing responses on unlabeled exposure trials (e.g., Clayards et al., 2008; Kleinschmidt & Jaeger, 2016; Theodore & Monto, 2019). This approach compares responses across different values of acoustic-phonetic cues (since the exposure inputs differed by exposure condition), so that assumptions baked into the analysis approach (e.g., linearity along the acoustic-phonetic continuum) can potentially bias the results. Here we avoid this issue by holding test stimuli constant (see also Kleinschmidt, 2020, Experiment 4).

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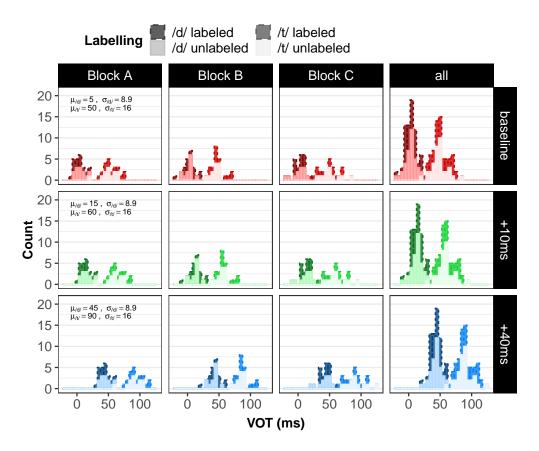


Figure 5. Histogram of voice onset times (VOTs) for each of the three exposure blocks A-C by trial type (/d/ or /t/, labeled or unlabeled) and exposure condition (baseline vs. +10 vs. +40). Each exposure block contained 12 labeled /d/, 12 labeled /t/, 12 unlabeled /d/, and 12 unlabeled /t/ trials, as well as 6 catch trials (not shown). Except for the shift in VOTs (+0, 10 or 40 ms VOT to each trial), the VOT distribution of these trials was identical across exposure conditions. The order of exposure blocks A-C was counter-balanced across participants using a Latin-square design.

Team, 2022; RStudio Team, 2020, for details, see SI, ??). Psychometric models account for attentional lapses while estimating participants' categorisation functions. Failing to account for attentional lapses—while commonplace in research on speech perception (but see Clayards et al., 2008; Kleinschmidt & Jaeger, 2016)—can lead to biased estimates of categorization boundaries (Prins, 2011; Wichmann & Hill, 2001). For the present experiment, however, lapse rates were negligible (0.9%, 95%-CI: 0.4 to 1.5%), and all results replicate in simple mixed-effects logistic regressions (Jaeger, 2008).

Each psychometric model regressed participants' categorisation responses against the full factorial interaction of VOT, exposure condition, and block, while including the maximal random effect structure (see SI, ??. Figure 6 summarizes the results that we describe in more detail next.

Panels A and B show participants' categorisation responses during exposure and test blocks, along with the categorisation function estimated from those responses via the mixed-effects 292 psychometric models. These panels facilitate comparison between exposure conditions within each 293 block. Panels C and D show the slope and point of subject equality (PSE)—i.e., the point at 294 which participants are equally likely to respond "d" and "t"—of the categorisation function across 295 blocks and conditions. These panels facilitate comparison across blocks within each exposure 296 condition. Here we focus on the test blocks, which were identical within and across exposure 297 conditions. Analyses of the exposure blocks are reported in the SI (??), and replicate all effects 298 found in the test blocks. 299

We begin by presenting the overall effects, averaging across all test blocks. This part of our 300 analysis matches previous work, which has focused on the overall effect of exposure across the 301 entire experiment ('batch tests,' e.g., Clayards et al., 2008; Kleinschmidt & Jaeger, 2016; Nixon et 302 al., 2016; Theodore & Monto, 2019) and/or during a single post-exposure test block (e.g., 303 Kleinschmidt, 2020). Then we turn to the goals of this study—to characterize the incremental 304 changes in participants' categorisation responses as a function of exposure and, in particular, to 305 test 1) whether we replicate the sublinear effects of exposure observed in previous work under the 306 ecologically more valid stimuli and distributions employed in the present work, and 2) whether we 307 can begin to distinguish between the predictions of the model learning and selection hypotheses. 308

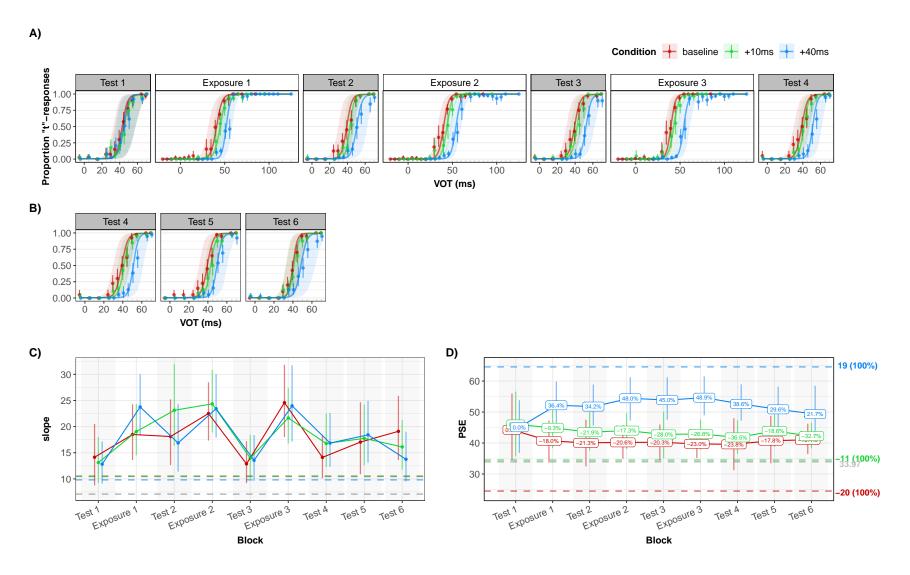


Figure 6. Summary of results. Panel A: Changes in listeners psychometric categorisation functions as a function of exposure, from Test 1 to Test 4 with all intervening exposure blocks (only unlabelled trials were included in the analysis of exposure blocks since labelled trials provide no information about listeners' categorization function). Point ranges indicate the mean proportion of "t"-responses and their 95% bootstrapped CI. Lines and shaded intervals show the MAP predictions and 95% posterior CIs of a Bayesian mixed-effects psychometric model fit to participants' responses. Panel B: Same as Panel A but for the final three test blocks without intervening exposure. Test 4 is shown as part of both Panels A and B. Panels C & D: Changes across blocks in the slope and boundary (point-of-subjective-equality, PSE) of the categorisation functions shown in Panels A-B. Point ranges represent the posterior means and their 95% CI. Dashed reference lines show the intercepts and PSEs that naive (non-rational) learner would be expected to converge against after sufficient exposure (on ideal observer model that knows the exposure distributions)

2.2.1 Does exposure affect participants' categorisations (averaging across all blocks)?

We first used the psychometric mixed-effects model to assess whether the exposure conditions had 311 the expected effects across all test blocks relative to each other. Unsurprisingly, participants were 312 more likely to respond "t" the larger the VOT 313 $(\hat{\beta} = 15.68, 90\% - \text{CI} = [13.149, 18.4], BF = 7999, p_{nosterior} = 1)$. Critically, exposure affects 314 participants' categorisation responses in the expected direction. Marginalizing across all blocks, 315 participants in the +40 condition were less likely to respond "t" than participants in the +10316 condition ($\hat{\beta} = -2.43,~90\% - \text{CI} = [-3.541, -1.363],~BF = 443.4,~p_{posterior} = 0.998)$ or the 317 baseline condition ($\hat{\beta} = -3.39,~90\%$ –CI = [-4.969, -1.93], $BF = 332.3,~p_{posterior} = 0.997$). 318 There was also evidence—albeit less decisive—that participants in the +10 condition were less 319 likely to respond "t" than participants in the baseline condition 320 $(\hat{\beta}=-0.97,~90\%-\text{CI}=[-2.241,0.298],~BF=9.2,~p_{posterior}=0.902).~\text{That is, the}~+10~\text{and}~+40~\text{cm}$ 321 conditions resulted in categorisation functions that were shifted rightwards compared to the 322 baseline condition, as also visible in Figures 6. 323 This replicates previous findings that exposure to changed VOT distributions changes 324 listeners' categorization responses (for /b/-/p/: Clayards et al., 2008; Kleinschmidt, 2020; 325 Kleinschmidt & Jaeger, 2016; for /g/-/k/, Theodore & Monto, 2019). Having established that 326 exposure affected categorization, we turn to the questions of primary interest. Incremental 327 changes in participants' categorisation responses can be assessed from three mutually 328 complementing perspectives. First, we compare how exposure affects listeners' categorisation 329 responses relative to other exposure conditions. This tests how early in the experiment differences 330 between exposure conditions began to emerge. Second, we compare how exposure affects listeners' 331 categorisation responses within each condition relative to listeners' responses prior to any 332 exposure. This assesses how the exposure conditions relate to participants' prior expectations. 333 Most importantly, however, it tests the subtly different predictions of the model learning and 334 selection hypotheses—whether changes in listeners' categorisation responses are strongly 335 constrained. Third and finally, we compare changes in listeners' responses to those expected from 336 an ideal observer that has fully learned the exposure distributions. This tests whether the 337

sublinear effects observed in Kleinschmidt and Jaeger (2016) replicate in our repeated
exposure-test paradigm with the improvements the present study makes to ecological validity.

2.2.2 Comparing across exposure conditions: How quickly does exposure begin to affect participants' responses?

Figure 6A suggests that differences between exposure conditions emerged early in the experiment: 342 already in Test 2, listener's categorisation functions seem to be shifted rightwards (larger PSEs) in the +40 condition compared to the +10 condition, and in the +10 condition compared to the 344 baseline condition. This is confirmed by the Bayesian hypothesis tests summarized in Table 1. 345 Prior to any exposure, during Test 1, participants' responses did not differ across exposure condition (all BFs > XXX). After exposure to only 24 /d/ and 24 /t/ stimuli, during Test 2, 347 participants' responses differed between exposure conditions (BFs > 17.35). The difference 348 between the +40 condition and the +10 or baseline condition kept increasing with exposure up to Test 4. Additional hypothesis tests in Table 2 show that the change from Test 1 to 2 was largest 350 (BF = 27.8), followed by the change from Test 2 to 3 (BF = 19.2), with only minimal changes 351 from Test 3 to 4 (BF = 1.7). Qualitatively paralleling the changes across blocks for the +40352 condition, the change in the difference between the +10 and baseline conditions was largest from 353 Test 1 to 2 (BF = 13.5), and then somewhat decreased from Test 2 to Test 4 (BFs < 4). The 354 comparison across exposure conditions thus suggests that changes in listeners' categorisation 355 responses emerged quickly—indeed, they were present already during the first exposure block (see SI, ??)—but then leveled off. The comparison across exposure conditions also yields one result 357 that is, at first blush, surprising: while the difference between the +10 and the baseline condition 358 emerged already after the first exposure block, this difference decreased, rather than increased, with additional exposure from Test 2 to 3 (see second row of Table 2). We return to this effect 360 below. 361

Tables 1 and 2 also reveal the consequences of repeated testing. The difference between exposure conditions decreased from Test 4 to 6 (BFs > 4.3; see also Figure 6B & D). On the final test block, the +10 condition did not differ any longer from the baseline condition. Only the differences between the +40 condition relative to the +10 and baseline conditions persisted, albeit

substantially reduced compared to Test 4. This pattern of results replicates previous findings that repeated testing over uniform test continua can undo the effects of exposure (Cummings & 367 Theodore, 2023; Liu & Jaeger, 2018, 2019), and extends them from perceptual recalibration 368 paradigms to distributional learning paradigms (see also Kleinschmidt, 2020). One important 369 methodological consequence of these findings is that longer test phases do not necessarily increase 370 the statistical power to detect effects of adaptation (unless analyses take the effects of repeated 371 testing into account, as in the approach developed in Liu & Jaeger, 2018). Analyses that average 372 across all test tokens—as remains the norm—are bound to systematically underestimate the 373 adaptivity of human speech perception. 374

Table 1 When did exposure begin to affect participants' categorization responses? When, if ever, were these changes undone with repeated testing? This table summarizes the simple effects of the exposure conditions for each test block.

Hypothesis	Estimate	SE	90%-CI	BF	$p_{posterior}$				
Test block 1 (pre-exposure)									
+10 vs. baseline	-0.39	0.94	[-2.096, 1.403]	1.99	0.66				
+40 vs. +10	0.20	0.86	[-1.359, 1.849]	0.68	0.40				
+40 vs. baseline	-0.19	1.11	[-2.377, 2.041]	1.32	0.57				
Test block 2									
+10 vs. baseline	-2.12	1.12	[-4.334, -0.109]	22.12	0.96				
+40 vs. +10	-2.10	1.21	[-4.333, 0.071]	17.35	0.95				
+40 vs. baseline	-4.22	1.47	[-7.048, -1.624]	80.63	0.99				
Test block 3									
+10 vs. baseline	-0.88	0.69	[-2.244, 0.417]	7.98	0.89				
+40 vs. +10	-3.26	0.96	[-5.164, -1.624]	169.21	0.99				
+40 vs. baseline	-4.15	1.11	[-6.371, -2.226]	162.26	0.99				
Test block 4									
+10 vs. baseline	-1.08	0.99	[-3.017, 0.947]	5.46	0.84				
+40 vs. +10	-4.02	1.09	[-6.043, -2.284]	420.05	1.00				
+40 vs. baseline	-5.10	1.43	[-7.839, -2.542]	132.33	0.99				
Test block 5 (no additional exposure)									
+10 vs. baseline	-1.50	0.86	[-3.08, 0.086]	16.24	0.94				
+40 vs. +10	-2.98	1.08	[-5.01, -1.205]	130.15	0.99				
+40 vs. baseline	-4.10	1.52	[-6.811, -1.436]	73.77	0.99				
Test block 6 (no additional exposure)									
+10 vs. baseline	-0.14	0.88	[-1.829, 1.456]	1.28	0.56				
+40 vs. +10	-2.03	0.91	[-3.852, -0.396]	34.71	0.97				
+40 vs. baseline	-3.15	1.39	[-5.754, -0.515]	31.39	0.97				

Table 2
Was there incremental change from test block 1 to 4? Did these changes dissipate with repeated testing from block 4 to 6? This table summarizes the interactions between exposure condition and block, whether the differences between exposure conditions changed from test block to test block.

Hypothesis	Estimate	SE	90%-CI	BF	$p_{posterior}$
Difference in $+10$ vs. baseline					
Block 1 to 2: increased Δ_{PSE}	-1.40	0.92	[-3.065, 0.199]	13.52	0.93
Block 2 to 3: increased Δ_{PSE}	0.85	0.98	[-1.113, 2.775]	0.25	0.20
Block 3 to 4: increased Δ_{PSE}	-0.01	0.92	[-1.838, 1.885]	1.02	0.50
Block 1 to 4: increased Δ_{PSE}	-0.58	1.54	[-3.652, 2.483]	1.82	0.64
Block 4 to 5: decreased Δ_{PSE}	-0.38	0.71	[-1.734, 1.091]	0.42	0.30
Block 5 to 6: decreased Δ_{PSE}	1.25	0.77	[-0.143, 2.723]	13.95	0.93
Block 4 to 6: decreased Δ_{PSE}	0.86	0.97	[-0.921, 2.908]	4.30	0.81
Difference in $+40$ vs. $+10$					
Block 1 to 2: increased Δ_{PSE}	-2.05	1.03	[-3.89, -0.231]	27.78	0.96
Block 2 to 3: increased Δ_{PSE}	-1.79	1.06	[-3.688, -0.001]	19.15	0.95
Block 3 to 4: increased Δ_{PSE}	-0.39	1.18	[-2.629, 1.624]	1.70	0.63
Block 1 to 4: increased Δ_{PSE}	-4.28	1.53	[-7.158, -1.722]	101.56	0.99
Block 4 to 5: decreased Δ_{PSE}	1.41	1.07	[-0.541, 3.319]	8.66	0.90
Block 5 to 6: decreased Δ_{PSE}	0.60	0.94	[-1.271, 2.311]	2.79	0.74
Block 4 to 6: decreased Δ_{PSE}	1.99	1.25	[-0.418, 4.338]	12.24	0.92
Difference in $+40$ vs. baseline					
Block 1 to 2: increased Δ_{PSE}	-3.44	1.13	[-5.612, -1.371]	87.89	0.99
Block 2 to 3: increased Δ_{PSE}	-0.96	1.33	[-3.488, 1.549]	3.32	0.77
Block 3 to 4: increased Δ_{PSE}	-0.42	1.45	[-3.303, 2.249]	1.56	0.61
Block 1 to 4: increased Δ_{PSE}	-4.85	2.16	[-9.019, -0.955]	36.04	0.97
Block 4 to 5: decreased Δ_{PSE}	1.03	1.22	[-1.254, 3.372]	3.92	0.80
Block 5 to 6: decreased Δ_{PSE}	1.86	1.12	[-0.329, 3.955]	13.18	0.93
Block 4 to 6: decreased Δ_{PSE}	2.88	1.56	[-0.178, 5.939]	16.13	0.94

2.2.3 Comparing within exposure conditions: How quickly does exposure begin to affect participants' responses?

Next, we compared how exposure affects listeners' categorisation reponses within each condition relative to listeners' responses prior to any exposure. These changes are summarised for the slope and PSE in Figure 6C & D, respectively. This visualization makes apparent two aspects of participants' behavior that were not readily apparent in the statistical comparisons we have summarized so far. First, while the PSEs for the +40 and +10 conditions were shifted rightwards compared to the baseline condition, both the +10 and the baseline condition actually shift leftwards relative to their pre-exposure starting point in Test 1. This is confirmed by Bayesian

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hypothesis tests summarized in Table ??.

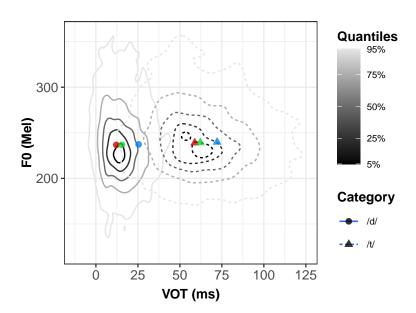


Figure 7. Placement of exposure stimuli relative to an estimate of typical phonetic distributions for XXX word-initial /d/ and /t/ productions in L1-US English (based on 92 talkers in Chodroff & Wilson, 2018). The outermost contour of each category shows the 95% density quantile. Points show the category means of the exposure condition.

To understand this pattern, it is helpful to relate our exposure conditions to the 385 distribution of VOT in listeners' prior experience. Figure 7 shows the mean and covariance of our exposure conditions relative to the distribution of VOT by talkers of L1-US English (based on 387 Chodroff & Wilson, 2018). This comparison offers an explanation as to why the baseline 388 condition (and to some extent the +10 condition) shift leftwards with increasing exposure, 389 whereas the +40 condition shifts rightwards: relative to listeners' prior experience our baseline 390 condition actually presented lower-than-expected category means; of our three exposure 391 conditions, only the +40 condition presented larger-than-expected category means. That is, once 392 we take into account how our exposure conditions relate to listeners' prior experience, both the 393 direction of changes from Test 1 to 4 within each exposure condition, and the direction of 394 differences between exposure conditions receive an explanation. 395

Second, the reason for the slight decrease in the difference between the +10 and baseline conditions observed in Tables ?? and 2 (visible in Figure 6D as the decreasing difference between the green and red line) is *not* due to a reversal of the effects in the +10 condition. Rather, both

conditions are changing in the same direction but the baseline condition stops changing after Test 2, which reduces the difference between the +10 and baseline conditions (see Table ??). The 400 comparison across blocks thus suggests a rather uniform picture across all exposure conditions: 401 participants' responses initially changed rapidly with exposure; with increasing exposure, these 402 changes did not only slow down but seem to hit a hard constraint. Participants in the 403 leftwards-shifted baseline condition did not exhibit any further changes in their categorisation 404 responses beyond Test 2. Similarly, participants in the rightwards-shifted +40 condition did not 405 exhibit any further changes in their categorisation responses beyond Test 3. Only participants in 406 the leftward-shifted +10 condition still exhibit changes across blocks even form Test 3 to 4. But, 407 perhaps tellingly, those participants also never reached the degree of shift that was evident in the 408 baseline condition.

410 2.2.4 Constraints on cumulative changes

Finally, Figures 6C & D also compare participants' responses against those of an ideal observer that has fully learned the exposure distributions.

413 3 General discussion

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- discuss consequences of findings for other accounts (decision-making; normalization)
- discuss fact that test stimuli deviate from exposure stimuli to different extent. on the one
 hand, it's just 1/4 of all trials. on the other hand, we do see relatively systematic changes in
 slopes each time we test. so there is evidence that even these 12 trials can affect
 categorisation slopes (though it is worth keeping in mind that this is a comparison across
 different sets of stimuli). could this explain shrinkage? unlikely since it wasn't the case in
 kleinschmidt and jaeger. could it explain the constraint on adaptation? that's less clear. we
 can, however, compare the relative mean of exposure and test.
 - could some form of moving window with historical decay explain the findings? On the one hand if the moving window is very small, that would not explain why we do see some cumulative changes across blocks (window must be at least 48 + 12 = 60 trials). on the

- other hand, the qualitative changes in the PSEs and slopes suggest that 12 trials can be
 enough to change some aspects of the categorisation function. it's thus *possible* that
 something that ways recent input much more strongly but also considers less recent input
 beyond 48 trials might explain the overall pattern.
- discuss potential that observed adaptation maximizes accuracy under the choice rule. use

 psychometric function fit during unlabeled exposure trials to calculate accuracy (not

 likelihood) on labeled trials under criterion and under proportional matching decision rules.

 compare against accuracy if ideal observers categorization functions are used instead.

3.1 Methodological advances that can move the field forward

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