

## **UC Merced**

### **Proceedings of the Annual Meeting of the Cognitive Science Society**

#### **Title**

Allocation of attention during auditory word learning

#### **Permalink**

<https://escholarship.org/uc/item/3xn7d1kn>

#### **Journal**

Proceedings of the Annual Meeting of the Cognitive Science Society, 38(0)

#### **Authors**

Apfelbaum, Keith S.

Sloutsky, Vladimir

#### **Publication Date**

2016

Peer reviewed

# Allocation of attention during auditory word learning

**Keith S. Apfelbaum (apfelbaum.3@osu.edu)**

Department of Psychology, 1835 Neil Ave.  
Columbus, OH 43210 USA

**Vladimir Sloutsky (sloutsky.1@osu.edu)**

Department of Psychology, 1835 Neil Ave.  
Columbus, OH 43210 USA

## Abstract

The deployment of selective attention has been studied in depth as a mechanism of visual categorization for decades. However, little work has investigated how attentional mechanisms operate for non-visual domains, and many models of categorization tacitly presume domain-general attention use. In three experiments, we investigated whether learners deploy attention to novel auditory features when learning novel words in a similar fashion to the prevailing visual categorization findings. These studies yielded evidence of non-isomorphism, as selective attention in the auditory domain shows high context specificity, in contrast to the wide generalization of attention in the visual domain.

**Keywords:** selective attention; auditory attention; categorization; category learning; word learning

## Introduction

Selective attention plays a crucial role in efficient categorization. Selective attention allows an organism to focus on features that reliably differentiate items from different categories, and ignore irrelevant features. By using only relevant features, organisms can efficiently classify items (i.e., decide what category the items belong to) without interference from irrelevant information. Classic findings in category learning show that adult learners readily and flexibly apply selective attention to learn category structures (Shepard, Hovland, & Jenkins, 1961). Attending selectively to features that are more predictive of category membership drastically improves learning compared to relying on all features equally. Such effects are thought to occur regardless of the type of feature; as long as features are not integral, learners readily show selective attention to the features (Best, Yim, & Sloutsky, 2013; Kruschke, 2003).

Selective attention's benefit for category learning is intuitive: in any category learning task where some features are relevant and others are irrelevant, a learner is best served by ignoring the irrelevant ones. However, despite this general benefit of selective attention, attention could be deployed in any number of ways: it could operate by changing attention to entire dimensions, or by shifting attention to regions within a dimension; it could be a finite resource, such that increased attention to one dimension necessitates decreased attention to another, or dimensions could be independent; it could readily generalize across contexts, or be tightly linked to contexts; and so on. Critically, these differences could emerge across sensory

domains – for example, visual category learning may differ from auditory lexical categories. The goal of research presented here is to test the isomorphism of mechanisms of categorization across modalities by examining how selective attention operates in auditory lexical categorization.

The bulk of research on selective attention has relied on visual stimuli. Although these studies are extremely informative, they leave a critical question of how categorization proceeds in non-visual domains. For example, little work has investigated selective attention in auditory learning of phonological or lexical categories. Understanding selective attention in this domain is critical to elucidating the nature of categorization. Isomorphism of selective attention would rapidly broaden our understanding of the processes of auditory categorization. Studying attention in the visual domain is simpler in many respects, such as the ability to explicitly measure attention through eye-tracking (Rehder & Hoffman, 2005). Similarly use of auditory tasks, such as measuring auditory processing in young children during sleep, could help answer visual categorization questions. However, a lack of isomorphism would suggest a need for in depth investigations of auditory attention, akin to those in the visual domain, to understand points of demarcation between domains, and to describe the mechanisms of auditory category learning.

Coarse grains of analysis suggest parallels between attention in the two domains. Language learners perform a type of dimensional attention to emphasize relevant dimensions and down-weight irrelevant ones (Apfelbaum & McMurray, 2015; Francis & Nusbaum, 2002; Toscano & McMurray, 2010), akin to dimensional weighting in visual categorization tasks (e.g., Nosofsky, 1986). Additionally, language development may pass from early, holistic representations of multiple stimulus features to more selective, phonetic-based representations (Werker & Curtin, 2005), parallel to the shift from distributed to selective attention in visual category learning (Sloutsky, 2010).

However, several domain differences may result in differential use of attention. Visual attention can rely on physical reorientation of the eyes to filter out irrelevant visual features; the auditory system lacks such physical means of selection. Additionally, auditory lexical categories rely on highly overlearned phonetic features; the same small set of features is used to differentiate all words throughout the lifespan of a monolingual speaker; visual categories include a wider variety of features, and sometimes even necessitate creation of novel features on the fly (Schyns,

Goldstone, & Thibaut, 1998). Finally, the temporal nature of auditory stimuli may encourage flexible attention deployment; static visual stimuli allow resampling information after initial filtering, whereas ignored auditory information may be unavailable if it later proves relevant.

The nature of selective attention use for auditory lexical categories thus remains an open empirical question. Although some work has demonstrated that selective attention occurs within this domain (Francis & Nusbaum, 2002; Holt & Lotto, 2010; Idemaru & Holt, 2011), no studies have examined if this attention is accomplished in the same manner as in visual categorization. The present experiments offer initial insight into the validity of an amodal theory of selective attention that subserves both visual and auditory-lexical category learning.

## Experiment 1

Selective attention during category learning is signaled by increased attention to one dimension accompanied by decreased attention to other dimensions. Measuring the deployment of selective attention relies on tracking either how learners attend to features during processing directly, such as with eye-tracking (Rehder & Hoffman, 2005), or inferring attention from performance measures, such as learning curves or discrimination thresholds (Kruschke, 2003). A challenge for gauging isomorphism across domains is using a task that allows comparable dependent variables; although eye-tracking allows direct measure of visual selective attention, no comparable direct measure of attention in the auditory domain is possible.

Additionally, the features themselves are not directly comparable. Auditory features operate differently (e.g. their temporal nature) and may be processed fundamentally differently. Attempting to equate features across domains is speculative at best. Instead, we emphasize qualitative comparisons: patterns of selective attention are consistent across different visual features, so differences that arise in our selection of auditory features would signal a diversion from the constant visual effects.

We thus used an inferential approach to gauging auditory selective attention, allowing ready comparison with patterns seen previously in the visual domain. Visual studies typically show rapid optimization to relevant category features, and concomitant decreased attention to irrelevant dimensions (Best, Yim, & Sloutsky, 2013). This pattern exhibits highlighting or down-weighting entire dimensions; when attention is allocated to a dimension in one context or one task, this pattern generalizes across contexts and values of the dimensions (Best et al., 2013; Kruschke, 2003).

We adapted the learned inattention paradigm to study selective attention allocation in the auditory lexical domain. We measured how discrimination thresholds for novel phonological contrasts changed based on their relevance for an auditory category learning task. Specifically, we sought evidence that learners improve discrimination of contrasts that are relevant to category learning, and simultaneously decline in discrimination of category irrelevant contrasts.

## Methods

**Participants** Data from 56 participants were included in analysis. The participants received partial course credit for a psychology course at Ohio State University. All reported being native speakers of English, and all had normal hearing and normal or corrected-to-normal vision. An additional 14 participants failed to complete the study due to computer error, exceeding time limitations to complete the task, or failure to learn the categories within 140 trials.

**Stimuli** Two 11-step continua were generated based on a single recording of the non-word *dubo*. The first continuum derived from adjusting the duration of the first vowel in *dubo*; the second consisted of different pitch patterns on the second vowel. These features were selected because they are not primary cues to phonetic distinctions in English; learners are more likely to show changes in attention to these features than primary phonetic features with which they have a lifetime of experience.

The continua were generated by excising the vowels from the recording, and then manipulating them to create equal-spaced steps before re-splicing the vowels back into the original recordings. The vowel-duration continuum on the first vowel consisted of durations ranging from 66 ms to 152 ms in approximately 8.5 ms steps. For the pitch continuum on the second vowel, all steps had a vowel-initial pitch of 184 ms. At the lowest step, this pitch slowly fell to 130 Hz; at the highest step it rose to 233 Hz. Pilot testing showed that these step sizes resulted in approximately equal discrimination. We fully crossed the two continua, creating 121 unique stimuli (11 vowel-one durations X 11 vowel-two pitches). The stimuli were visually and auditorily inspected to ensure that they sounded natural and were free of artifacts from the acoustic manipulations.

**Procedure** The procedure used a pre-test, training, post-test design. Pre- and post-test were identical; these segments measured participants' discrimination thresholds separately for each contrast to determine whether discrimination was affected by categorization training. Specifically, we measured whether discrimination improved for a contrast that was relevant for categorization and simultaneously decreased for a contrast that was irrelevant. For pre-and post-test trials, participants were required to identify whether two stimuli were acoustically identical or different. On *different* trials, stimuli were chosen using an adaptive staircase procedure to estimate discrimination thresholds. Same and different trials were randomly interleaved. Trials for each staircase continued until the participant (1) reversed accuracy on different trials four times; (2) successfully discriminated the smallest possible distinction (i.e. a one-step difference); or (3) failed to discriminate the largest possible distinction.

Discrimination thresholds of the two vowel contrasts were tested independently; when testing discrimination of the duration contrast, the pitch contrast was held constant, so discrimination could only emerge on the basis of a single contrast. For each contrast, discrimination was measured

from the lowest step and from the highest step; the discrimination threshold for that contrast was the average estimated threshold from each of these steps. There were thus four separate estimated thresholds (two each for the duration and the pitch contrast). The staircases for the four threshold estimations were randomly interleaved.

Training consisted of teaching participants two categories defined by one of the novel features. One of the two contrasts was selected as relevant to category identity, and the other was irrelevant. Assignment of which contrast was relevant was counterbalanced across participants: 28 participants had vowel-one duration relevant and the other 28 had vowel-two pitch relevant. Participants were informed that they were going to learn two words from a language that uses different sounds than English. Each trial, they saw two visually distinct cartoon alien creatures and heard a stimulus; they clicked on the alien they believed the word identified, and then received feedback.

The relevant dimension determined which alien was correct; one alien was associated with the lowest step on this dimension, and the other with the highest step. No other steps of the relevant contrast were presented. The step for the irrelevant dimension was randomly selected on each trial, so this dimension was unpredictable of category membership. Participants continued receiving trials until they reached 80% accuracy across a 40-trial window. If they failed to reach this criterion in 140 trials, they were removed from the experiment and their data were excluded.

After categorization training, participants completed the post-test. This test was conducted exactly as in the pre-test, allowing comparison of pre-training thresholds with those after one dimension was made relevant for categorization.

## Results and discussion

We first analyzed performance during categorization trials. Participants quite quickly reached the accuracy criterion, with a mean trials-to-criterion of 47.2 ( $SD=19.0$ ). Thirty-nine of the 56 participants reached criterion by the 40<sup>th</sup> trial. Participants for whom duration was relevant reached criterion slightly more quickly than those for whom pitch was relevant ( $M=42.2$  and  $52.1$ , respectively;  $t(54)=-1.99$ ,  $p=.052$ ), suggesting that the pitch contrast may have been slightly more difficult than the duration contrast.

The critical analysis of discrimination thresholds showed a classic pattern of learned inattention (Figure 1); discrimination of the relevant contrast became more sensitive after training (as indicated by decreased discrimination thresholds), and the irrelevant contrast showed poorer discrimination after training. We analyzed these data using mixed effects models (ANOVA yielded similar results). The DV was step-size of the discrimination threshold for the contrast as estimated from the staircase procedure. We contrast-coded feature type (irrelevant:  $-.5$ ; relevant:  $+.5$ ) and test-type (pre-test:  $-.5$ ; post-test:  $+.5$ ) for use as fixed factors. Participant was included as a random intercept, as was the slope of relevance for participants. Including which feature was relevant as a random intercept

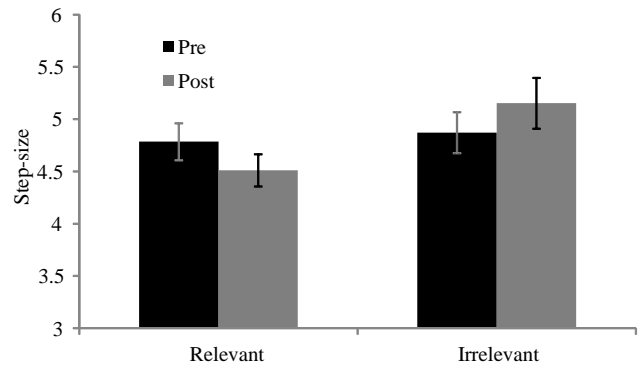


Figure 1. Mean step size of reversals as a function of relevance and test-type. Error bars represent the standard error of the mean.

did not improve model fit by  $\chi^2$  test ( $p=.31$ ), so this was not included in the analyses; including this random effect produced extremely similar results.

Results confirmed the pattern seen in Figure 1. Specifically, there was no main effect of feature type ( $B=.363$ ,  $SE=.299$ ,  $t(55)=-1.22$ ,  $p=.23$ ) nor of test type ( $B=.0011$ ,  $SE=.082$ ,  $t(168)=.014$ ,  $p=.99$ ). However, there was a significant interaction of feature type and test type ( $B=-.56$ ,  $SE=.16$ ,  $t(168)=-3.43$ ,  $p<.001$ ). Simple effects testing showed a significant decrease in discrimination threshold for the relevant feature ( $B=-.28$ ,  $SE=.11$ ,  $t(839)=-2.59$ ,  $p=.0098$ ), and a significant increase in discrimination threshold for the irrelevant feature ( $B=.28$ ,  $SE=.12$ ,  $t(839)=2.30$ ,  $p=.022$ ).

The results present evidence for selective attention in learning auditory lexical categories defined by novel features. After training, participants' ability to recognize small acoustic changes in a feature that had been relevant for categorization improved, whereas their ability to recognize changes in a second feature that was irrelevant declined. This pattern of results mirrors patterns from visual category learning (Best et al., 2013; Dopson, Esber, & Pearce, 2010; Hoffman & Rehder, 2010; Kruschke & Blair, 2000; Mackintosh & Little, 1969).

Although these results are suggestive of isomorphism of selective attention across domains, evidence of generalization is necessary before concluding that isomorphism exists. Findings in the visual domain demonstrate attention to entire dimensions; when a dimension is attended, processing benefits persist in later tasks, even for new values of the dimension and new contexts. Experiment 1 used identical stimuli during training and test – we tested the same values of the same features in the same contexts. To further investigate selective attention in the auditory lexical domain, we considered two types of generalization. Experiment 2 examined generalization of selective attention to a novel voice (a change in irrelevant context). Experiment 3 examined generalization to a novel word (a change in relevant context).

## Experiment 2

Experiment 2 followed the design of Experiment 1, but incorporated a change in irrelevant context. Specifically, training was done in one voice, whereas testing was conducted in a different voice. The same words and features were used in the two segments, so learning could readily generalize if learners deploy attention to abstract dimensions. However, if selective attention operates in a context-specific manner, generalization may be unattested.

### Methods

**Participants** Data from 81 participants were included in the analysis of Experiment 2. Thirty-seven received male-voice stimuli during pre- and post-test, and female-voice stimuli during training; the remaining 44 received the reverse. Six additional participants were excluded from analysis for exceeding time limitations to complete the task, or failure to learn the categories within 140 trials.

**Stimuli** The female-voice stimuli were identical to those in Experiment 1. For the male-voice stimuli, we acoustically manipulated the female-voice stimuli to approximate a male voice. We used the Change Gender option in Praat, which scales the formant values in a stimulus. We found that a ratio of 1/1.1 altered the percept of talker gender without impacting clarity of the stimuli. We thus created a male-voice version of every stimulus from Experiment 1.

Although this method is less natural than recording two different talkers, it allows close control of the manipulated features. The Change Gender function does not impact duration or overall pitch, so the stimuli in the two voices maintained identical values of the features despite the percept of different voices. The distribution of cues was thus identical between the two stimulus sets; learners can thus generalize even on the basis of specific feature values, but must do so in a novel context.

**Procedure** The procedure was identical to Experiment 1, except that the voice used in pre- and post-test was the opposite gender as that used in training.

### Results and discussion

Analysis of the training portion of the study again showed very rapid learning ( $M=45.8$ ; 64 of 81 participants reached criterion by trial 40). No difference in speed of learning was seen between the voices used in training.

The discrimination thresholds showed sensitivity to category relevance, as the threshold decreased for the relevant feature (Figure 2). However, no concomitant increase in threshold was seen for the irrelevant feature; this feature also showed a (very small) decrease. We analyzed these data using a mixed effects model with similar structure to the one used in Experiment 1. In addition to the random effects used for that model, we added training voice as a random intercept, and a random slope of relevance for training voice. Including training voice instead as a fixed

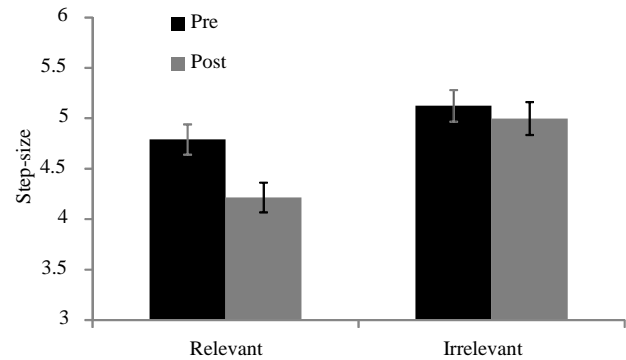


Figure 2. Mean step size of reversals as a function of relevance and test-type. Error bars represent the standard error of the mean.

factor yielded extremely similar results, with no main effects or interactions of training voice.

This analysis revealed a main effect for test type ( $B=-.35$ ,  $SE=.069$ ,  $t(2460.3)=-5.05$ ,  $p<.0001$ ), with lower thresholds at post-test than at pre-test. There was no effect of relevance ( $B=-.50$ ,  $SE=.28$ ,  $t(6.0)=-1.82$ ,  $p=.12$ ). However, there was a significant two-way interaction of test type and relevance ( $B=-.45$ ,  $SE=.14$ ,  $t(2460.3)=-3.24$ ,  $p=.0012$ ). Simple effects analyses used to investigate this interaction showed a significant effect of test type for the relevant contrast ( $B=-.57$ ,  $SE=.094$ ,  $t(1230.0)=-6.10$ ,  $p<.0001$ ); thresholds were lower at post-test than they were at pre-test. However, the model for the irrelevant feature showed no effect of test type ( $B=-.13$ ,  $SE=.10$ ,  $t(1230.3)=-1.23$ ,  $p=.22$ ); performance for the irrelevant feature was similar at pre-test and post-test.

These results differ from classic findings of learned inattention. Although the relevant feature showed evidence of improved processing, this was not accompanied by the expected drop in performance for the unattended feature. This finding is quite surprising; nearly all models of attention argue for a limited quantity of attention, such that attention to one dimension necessitates decreased attention to others. Our results violated this coupling, suggesting that attention in the auditory lexical domain may not engage the same coupling across dimensions.

Experiment 2 thus provided only partial evidence of isomorphism across domains. Learners generalized highlighting of a relevant dimension across talker voices, but did not simultaneously generalize learned inattention to the irrelevant dimension. This pattern suggests that attention in the auditory lexical domain may operate in a more context-specific manner than in the visual domain.

## Experiment 3

Experiment 3 examined generalization more thoroughly, by investigating generalization across a relevant context. Specifically, training and testing used the same features, but embedded in different words. During training, vowel duration and pitch contour were manipulated in one word (e.g. *dubo*), whereas testing employed these same features in a second word (e.g. *bugo*). This more directly measures

whether learners are deploying attention to abstract dimensions; for example, if they are learning about vowel duration in general, patterns of attention should generalize across lexical contexts. However, if attention is deployed in a context-sensitive manner, then attention to one word learned in training may not generalize to other words at test.

## Methods

**Participants** Data from 60 participants were included in the final analysis. Thirty participants were included in each training-word condition (*dubo* train/*bugo* test or vice versa). Data from five additional participants were not included in the final sample for exceeding time limitations to complete the task, or failure to learn the categories within 140 trials.

**Stimuli** The stimuli included the original stimuli from Experiment 1 using *dubo*, as well as new stimuli constructed using the same features and methods of generating these features, based on the word *bugo*. The new base word was recorded by the same talker in the same session. This second word includes the same vowels in similar phonological contexts (surrounded by voiced obstruents). As such, although generalization must occur across words, the contexts are quite similar, and the values of the features were quite similar. If generalization is unattested across these similar words and feature values, it is unlikely to arise across the much broader diversity of words in the language.

**Procedure** The procedure was identical to Experiment 1, except that different words were used in pre-/post-test and training.

## Results and discussion

Analysis of the training data again showed that participants rapidly reached the accuracy criterion ( $M=48.4$  trials; 42 of 60 participants reached criterion by the 40<sup>th</sup> trial).

Analysis of the critical pre- and post-test discrimination thresholds showed marked improvement in discrimination for *both* relevant and irrelevant contrasts (Figure 3). Statistical analyses were conducted using mixed effects

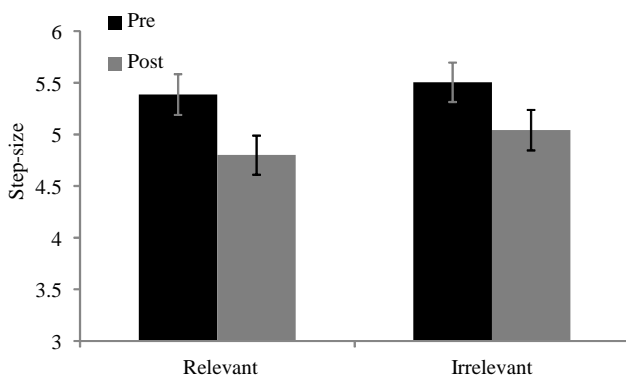


Figure 3. Mean step size of reversals as a function of relevance and test-type. Error bars represent the standard error of the mean.

models with similar structures to those in the prior experiments, but adding a random intercept of word used during training and a random slope of training word for which feature was relevant. Including word as a fixed factor instead yielded similar results, with no significant effects or interactions of word.

The model revealed a main effect of test type ( $B=-.53$ ,  $SE=.085$ ,  $t(1798.0)=-6.24$ ,  $p<.0001$ ), as discrimination thresholds declined from pre- to post-test. However, there was no effect of relevance ( $B=-.17$ ,  $SE=.47$ ,  $t(1.2)=-.37$ ,  $p=.76$ ), nor was the interaction significant ( $B=-.14$ ,  $SE=.17$ ,  $t(1798.0)=-.85$ ,  $p=.40$ ). The relevance of the features during training had no effect on discrimination performance, suggesting that category learning did not result in generalization of selective attention. Instead, performance improved similarly for relevant and irrelevant features.

These results demonstrate no generalization of selective across lexical contexts. Instead, sensitivity improves for both relevant and irrelevant features (perhaps because of learning about the task). Whereas visual category learning tasks show generalization of selective attention across contexts (e.g., Best et al., 2013; Kruschke, 2003), the auditory lexical domain seems to display much stronger context specificity.

## General Discussion

We examined the degree to which auditory lexical category learning exhibits isomorphic use of selective attention to visual category learning. Although we found evidence that selective attention aids learning of auditory lexical categories, its deployment proved more context sensitive than for visual categories. Learners in Experiment 1 highlighted relevant features and decreased attention to irrelevant features; however, this pattern only weakly generalized to a novel voice, and showed no apparent generalization to a novel word. Visual category learning shows ready generalization; in fact, visual category learning studies often use training in one context, and then measure continued selective attention in a new context (Best et al., 2013; Kruschke, 2003). This suggests a clear demarcation between the two domains.

Phonological information seems to generalize eventually; when learning novel words, learners bring prior learning about feature relevance to bear. If generalization were never attested, learners would have to learn for each word that features like voice are irrelevant. Yet our results show that at least initially, learners treat novel features with high context specificity. This specificity is similar to developmental evidence that infants may treat words as functionally independent, without generalizing features (Apfelbaum & McMurray, 2011; Werker & Curtin, 2005). However, these similar patterns of specificity among adults are surprising. In the visual domain, even for novel features learners exhibit patterns of learned inattention (Best et al., 2013). Generalized selective attention across contexts seems the default in vision. For auditory lexical categories, it appears to be non-default. This finding may lend credence

to theories of voice-specific priming, in which words are obligatorily processed with indexical information as part of the representation (Papesh, Goldinger, & Hout, 2016). Similar results suggest that talker information and phoneme information are asymmetrically related because of talker normalization processes (Mullennix & Pisoni, 1990); talker information may be difficult to ignore to focus on abstract features because these features are often altered by talker characteristics. However, these talker-specificity effects are less straightforward as an explanation of the lack of generalization across lexical contexts.

This context specificity may arise because of the closed-set nature of features used to differentiate lexical items. Languages use a relatively small set of phonemes to differentiate an enormous set of words. Listeners receive copious exposure to this small set, allowing learning of the relevant features to become quite entrenched. Processing features differently (as in the present study) may prove quite difficult. Indeed, inflexibility of processing speech features may be why learning the phonology of a second language is markedly difficult for adults (Jusczyk, 1993).

Yet even if such an explanation holds for why learners show poor generalization across contexts in these experiments, it nonetheless represents a departure from processing in the visual domain. Auditory lexical category learning may rely on a core set of inflexible features, whereas visual category learning is flexible in the face of novel features. Selective attention in the auditory lexical domain would thus operate within a constrained context for novel features, and only generalize for known features, instead of generalizing readily. As such, selective attention across these domains shows a lack of isomorphism; the way attention operates depends on the domain.

## References

- Apfelbaum, K. S., & McMurray, B. (2011). Using variability to guide dimensional weighting: Associative mechanisms in early word learning. *Cognitive Science, 35*(6), 1105–38. doi:10.1111/j.1551-6709.2011.01181.x
- Apfelbaum, K. S., & McMurray, B. (2015). Relative cue encoding in the context of sophisticated models of categorization: Separating information from categorization. *Psychonomic Bulletin & Review, 22*(4), 916–943. doi:10.3758/s13423-014-0783-2
- Best, C. A., Yim, H., & Sloutsky, V. M. (2013). The cost of selective attention in category learning: Developmental differences between adults and infants. *Journal of Experimental Child Psychology, 116*(2), 105–19. doi:10.1016/j.jecp.2013.05.002
- Deng, W., & Sloutsky, V. M. (2015). The Development of Categorization: Effects of Classification and Inference Training on Category Representation. *Developmental Psychology, 51*(3), 392–405.
- Dopson, J. C., Esber, G. R., & Pearce, J. M. (2010). Differences in the associability of relevant and irrelevant stimuli. *Journal of Experimental Psychology: Animal Behavior Processes, 36*(2), 258–267. doi:10.1037/a0016588
- Francis, A. L., & Nusbaum, H. C. (2002). Selective attention and the acquisition of new phonetic categories. *Journal of Experimental Psychology: Human Perception and Performance, 28*(2), 349–366.
- Hoffman, A. B., & Rehder, B. (2010). The costs of supervised classification: The effect of learning task on conceptual flexibility. *Journal of Experimental Psychology: General, 139*(2), 319–340. doi:10.1037/a0019042
- Holt, L. L., & Lotto, A. J. (2010). Speech perception as categorization. *Attention, Perception, & Psychophysics, 72*(5), 1218–1227. doi:10.3758/APP
- Idemaru, K., & Holt, L. L. (2011). Word recognition reflects dimension-based statistical learning. *Journal of Experimental Psychology: Human Perception and Performance, 37*(6), 1939–56. doi:10.1037/a0025641
- Jusczyk, P. W. (1993). From general to language-specific capacities: The WRAPSA model of how speech perception develops. *Journal of Phonetics, 21*, 3–28.
- Kruschke, J. K. (2003). Attention in learning. *Current Directions in Psychological Science, 12*(5), 171–175. doi:10.1111/1467-8721.01254
- Kruschke, J. K., & Blair, N. J. (2000). Blocking and backward blocking involve learned inattention. *Psychonomic Bulletin & Review, 7*(4), 636–645. doi:10.3758/BF03213001
- Mackintosh, N. J., & Little, L. (1969). Intradimensional and extradimensional shift learning by pigeons. *Psychonomic Science, 14*(1), 5–6.
- Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General, 115*(1), 39–61.
- Rehder, B., & Hoffman, A. B. (2005). Eyetracking and selective attention in category learning. *Cognitive Psychology, 51*, 1–41. doi:10.1016/j.cogpsych.2004.11.001
- Schyns, P. G., Goldstone, R. L., & Thibaut, J. P. (1998). The development of features in object concepts. *The Behavioral and Brain Sciences, 21*(1), 1–54.
- Shepard, R. N., Hovland, C. I., & Jenkins, H. M. (1961). Learning and memorization of classifications. *Psychological Monographs: General and Applied, 75*(13), 1–42. doi:10.1037/h0093825
- Sloutsky, V. M. (2010). From Perceptual Categories to Concepts: What Develops? *Cognitive Science, 34*(7), 1244–1286. doi:10.1111/j.1551-6709.2010.01129.x
- Toscano, J. C., & McMurray, B. (2010). Cue integration with categories: Weighting acoustic cues in speech using unsupervised learning and distributional statistics. *Cognitive Science, 34*(3), 434–464. doi:10.1111/j.1551-6709.2009.01077.x
- Werker, J. F., & Curtin, S. (2005). PRIMIR: A developmental framework of infant speech processing. *Language Learning and Development, 1*(2), 197–234.