Anticipation Effect after Implicit Distributional Learning

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Abstract

Distributional learning research has established that humans can track the frequencies of sequentially presented stimuli in order to infer the probabilities of upcoming events (e.g., Hasher & Zacks, 1984). Here, we set out to explore anticipation of a stimulus after implicit distributional learning. We hypothesize that as people learn the category frequency information implicitly, response times will scale according to the relative frequency of the stimulus category. Twelve adult participants viewed photographs of faces, tools, and buildings while performing a simple classification task. We found that response times significantly decreased with greater frequencies in the distribution of stimulus categories. This result suggested that distributional information about the internal representations of the stimuli could be learned and indicated the possibility that participants anticipated the stimuli proportional to the probability of the category appearing and thereby reduced response times for the more frequent categories.

Keywords: statistical learning; implicit distributional learning; anticipation; classification

Introduction

Although complicated and dynamic, our sensory environment contains regularities distributed both spatially and temporally. Previous studies have shown that humans can acquire information from a probabilistic structure, and they are able to predict the upcoming stimulus using distributional knowledge. In this study, we used behavioral methods to investigate anticipation prior to object classification after distributional learning of the object category frequencies.

People are known to be sensitive to the distributional information, and they are able to actively use this information to make complex inferences, such as identifying underlying structures in sequences. Explicit probabilistic information can aid human decision-making in many situations (Arkes, Dawes, & Christensen, 1986; Wiggs, 1993; Lin, Kung, & Lin, 1997). In addition to explicit distributional learning, in fact, it is well established in the fields of human development, language acquisition, attention, and perception that people are sensitive to implicit distributional information (e.g., Attneave, 1953; Fiser & Aslin, 2002; Hasher & Zacks, 1984; Saffran, Aslin, & Newport, 1996; Tryk,1968; Turk-Browne, Scholl, Chun, & Johnson, 2009; Pelucchi, Hay, & Saffran, 2009). In these studies, distributional information was not explicitly provided to participants, but the results showed that participants could track the stimulus input to infer its underlying causal structure and therefore make accurate predictions or judgments about which stimuli potentially fit or violate this structure. Thus, even when these statistical relationships are not explicitly presented and the stimuli are too numerous to be explicitly counted, people can discover an accurate distributional model of the input.

Particularly, classification tasks have been used to test implicit distributional learning (Forster & Chambers, 1973; Stanners, Forbach & Headley, 1971; Stanners, Jastrzembski, & Westbrook, 1975; Whaley, 1978). Classifying responses can reflect distributional learning processes, as learned items can be recognized and discriminated from other items faster than unfamiliar items can. For example, Whaley (1978) found that response times for word and non-word classification were substantially faster with high-frequency initial and final consonants than for words with low-frequency consonants in initial or final position or both. Although in the context of language, this finding shed lights on the correlation between implicit distributional learning and response times, and it demonstrated the methodology of using a classification task to test this correlation.

Response time has been used to measure anticipation in many studies (Haith, Hazan, & Goodman, 1988; Hinrichs & Krainz, 1970; Todorovic, van Ede, Maris, & de Lange, 2011; Turk-Browne, Scholl, Johnson, & Chun, 2010, Poulton, 1950). Some of these studies have found that when participants were instructed to predict the upcoming stimulus, response times were faster for correct predictions than for incorrect predictions (Bernstein & Reese, 1965; Hinrichs et al., 1970). This finding suggests that anticipation of an upcoming stimulus influences the response time in the subsequent trial.

However, the effect of adult observers' use of implicit distributional learning on anticipation of the category of an upcoming stimulus remains largely unexplored. Most studies have focused on effect of frequency information about stimulus-stimulus association (e.g. Conway & Christiansen, 2005; Kirkham, Slemmer, Johnson, 2002; O'Brien & Raymond, 2012; Olson & Chun, 2001; Turk-Browne, Jungé, Scholl, 2005), and little research have looked into the effect of the overall distributional information about the internal representation of the stimuli (e.g. the categorical representation of the object).

Here, we aimed to establish evidence for anticipatory representations of the category of the upcoming stimulus emerging from distributional learning. Turk-Browne et al. (2010) investigated implicit anticipation triggered by probabilistic information. Their behavioral result showed that when the participants observed and made classification responses to every trial, the participants reacted faster to the trials that can be predicted from their immediate preceded trials. Based on this finding, in the experiment, we measured participants' anticipation of an object category by measuring the response times in a sequential classification task. We examined the anticipatory effects of the underlying distribution and predicted that response times for classification would decrease with greater category frequencies, suggesting that as people learned the category distributional information implicitly, anticipation was scaled according to the probability of the category appearing.

Methods

Participants

Twelve participants were recruited (*mean age* = 20 years; *SD* = 1.7 years; 7 females, 5 males) and were compensated \$10 per hour. All participants were undergraduate students at the University of Rochester. All participants reported being right-hand dominant. The experiment took around 45 minutes to complete. The study procedures were approved by the Institutional Review Board of the University of Rochester, and participants received an informed consent document prior to the study.

Materials

We chose three categories of stimuli: faces, buildings, and tools. Each category has specific brain areas that reliably respond to one of these categories but not the others (Epstein & Kanwisher, 1998; Kanwisher, McDermott, & Chun, 1997; Chao & Martin, 2000). The images from each of these categories were grey-scaled and edited to be the same size (640 × 480 pixels) using Preview software in Mac OSX. The images appeared in the middle of a 27″ iMAC monitor with 1920 × 1080 resolution. The images appeared in the middle of the screen against a white background. Face images were acquired from the Chicago Face Database (Ma, Correl, & Wittenbrink, 2015); Building images were downloaded by Google Image search with the keywords "building" and "house"; Tool images were obtained from the BOSS database (Brodeur, Dionne-Dostie, Montreuil, & Lepage M, 2010).

The frequency of each category (60%, 30%, or 10%) was counterbalanced across six different distributional conditions using Latin Squares (Winer, 1962). This manipulation counterbalanced carryover effects between conditions and ensured that participants see each of the conditions in the study. We chose 60%, 30%, and 10% as frequencies considering the number of trials in each block (30 trials) and condition (90 trials). These frequencies produce integer instead of the decimal number of trials in each condition. The complete information about these six conditions is shown in Table 1.

Three adjacent buttons on the computer keyboard were marked as "F", "H" and "T". To exclude the motor-related confounds that were the interest of this study, the key mapping was counterbalanced across subjects. Subjects were asked to always use the same three fingers (index, middle, and ring fingers) for the same keys.

Table 1: Distribution of categories in each condition

	Faces	Buildings	Tools	Num. of Trials
Condition 1	60%	30%	10%	90
Condition 2	60%	10%	30%	90
Condition 3	10%	60%	30%	90
Condition 4	30%	60%	10%	90
Condition 5	10%	30%	60%	90
Condition 6	30%	10%	60%	90
Num. of Trials	180	180	180	540

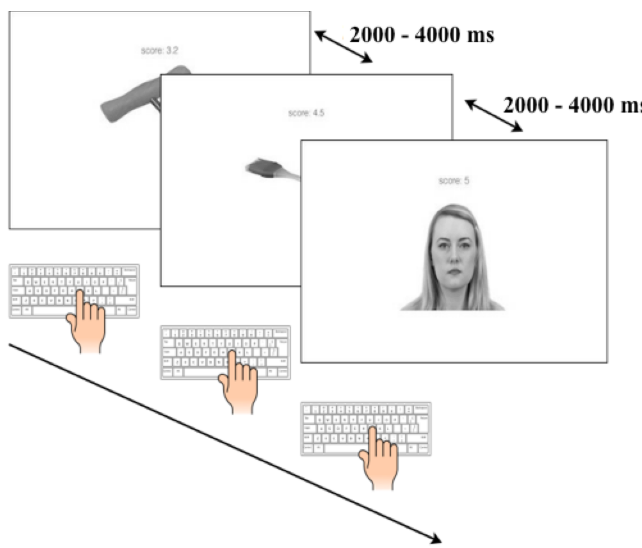


Figure 1: Illustration of the experiment experimental protocol of first three trials in one condition. After participants read the instructions, images appeared on the screen and participants responded accordingly by pressing corresponding buttons. A score would appear above the picture after the participant pressed a button.

Procedure

Subjects were asked to perform a simple classification task. The presentation of stimuli was programmed using MATLAB Psychophysics toolbox (Brainard, 1997; Kleiner, Brainard, Pelli, Ingling, & Murray, 2007; Pelli, 1997). The experiment took place in a behavioral testing cubicle. During each condition, the participants were instructed to press a designated key to indicate the category of each presented stimulus. A score was given based on the reaction time immediately after each response (zero for inaccurate or missing trials), and a total score was presented after each condition. The scores were presented in order to provide feedback and motivate participants to give faster and more accurate responses, and they were not used in the analysis. Stimulus-onset asynchrony (SOA; 2000, 4000, and 6000 ms) was varied to prevent participants from predicting when the next stimulus would appear on the screen. Each trial had a fixed image duration of 1000 ms, and the image would not disappear after a response was recorded. Inter-trial interval (ITI) varied based on the SOA of that trial. Each subject went through all 6 conditions. Each condition had 3 blocks, and each block displayed 30 images. In total 90 images were presented in each condition, and 540 images in the whole experiment. The breaks between blocks were 15000 ms, and the breaks between conditions were two minutes. Instructions between each condition were designed to cue the participants to the new distributional information of the next condition: "Thank you for finishing the task. Please take a short break. A new but similar task will start in two minutes." The illustration of the experiment experimental protocol of first three trials in one condition is shown in Figure 1.

Results

In total, 6480 responses were recorded (M = 521 ms; SD = 107 ms; *Accuracy* = 0.948). For analysis, we excluded the trials with incorrect responses or no responses. And across all participants, 336 out of 6480 trials (0.05%) were excluded for this reason. Paired two-tailed t-tests showed that for all twelve subjects, mean response times of block 2 for each condition were significantly less than those of block 1, t=2.255, p=0.038<0.05; average response times of block 3 for each condition were significantly less than those of block 1, t=2.585, p=0.019<0.05; but average response times of block 3 for each condition were not significantly less than average response times of block 2, t=-0.683, p=0.504. It is possible that subjects needed several trials to acquire the distributional information of the current condition and to replace the carryover distributional information from previous conditions. And after obtaining the current distributional information, the participants were able to perform the task using this knowledge. Thus, we excluded all trials from block 1 of each condition. The analyses only contained correct responses from block 2 and block 3. Mean, standard deviation, and accuracy of response times for each category in each frequency are shown in Table 2.

Using linear mixed-effects models in R, we compared response times for different stimuli in each distribution. We first used a 3-way interaction model (SOA × category × frequency), but did not find any significant 3-way interaction. Instead, a reduced 2-way interaction model (category × frequency + SOA × category + SOA × frequency) was estimated and reported in Table 3. Face was chosen as the arbitrary baseline category by R to prevent multi-collinearity in the indicator variables for the stimulus category.

SOA did not significantly interact with Frequency, and only marginally varied across Category (p = 0.07). A main effect of SOA was also significant (p = 0.006). Therefore, although SOA was not a variable of particular interest, we retained it in the model to control for the possible effects of the pre-stimulus waiting period on the anticipatory representation and thus on the change in response times.

Similarly, no main effect for Category was found, but we retained this term due to its significant interaction with Frequency (see below) and to account for Category-specific differences in baseline response rate (e.g., participants responded to faces faster than tools and buildings).

The main effect of frequency was highly significant (p < 0.001), consistent with our hypothesis that response times would differ as a function of the stimulus distribution. The post-hoc paired t-tests on subject-level mean response times found that response times indeed significantly decrease as the frequency of the stimulus category increased (60% vs. 30%: $t(11)$ = -6.08, p < 0.001; 30% vs. 10%: $t(11)$ = -5.01, p < 0.001).

The interaction between frequency and condition was also significant, so we examined the frequency effects specific to each category of the stimuli. We found that within each of the categories, response times generally decreased as its frequency increased (see Figure 2 for the summary of tests), although many of these tests would not survive correction for multiple comparisons. With the results from the linear mixed-effect models and the t-tests, we can conclude that this effect is in line with our hypothesis that participants' response times reduced proportionally to the increasing frequency of the category.

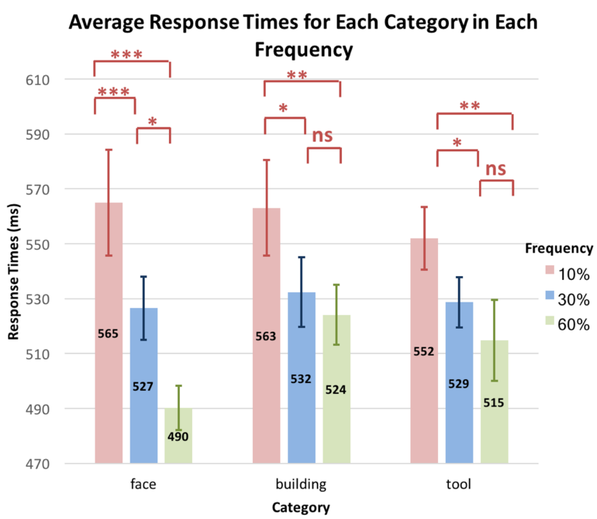
We also looked at the estimated slopes for the frequency × category interaction in the model (Figure 3), which was

Table 3: ANOVA performed on linear mixed-effects model with 2-way interactions

	SS	**MS**	**Num. DF**	**Den. DF**	***F***	***p*-value**
SOA	0.38	0.38	1	6119.5	7.644	0.006 **
Category	1.63	0.82	2	6119.3	0.676	0.509
Frequency	4.72	4.72	1	6119.5	40.628	<0.001 ***
Category × Frequency	0.34	0.17	2	6119.2	6.224	0.002 **
SOA: Category	0.14	0.07	2	6119.3	2.574	0.076 .
SOA: Frequency	0.05	0.05	1	6119.5	1.963	0.161

Notes. . p < .1; * p < .05; ** p < .01; *** p < .001

highly significant in the ANOVA. Steeper slopes indicate a stronger influence of frequency on that category. It is clear that frequency influenced face more than it influenced tool, and it influenced tool more than it influenced building (*slope(face)* = -2.123; *slope(building)* = -1.156; *slope(tool)* = -1.395).



Notes. * p < .05; ** p < .01; *** p < .001;
ns: no significance

Figure 2: Average response times for each category in each frequency. The error bars were indicated by one standard error of the mean.

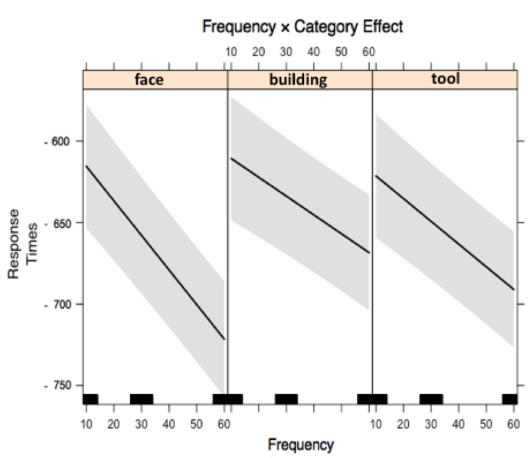


Figure 3: Frequency × Category Effect

Discussion

In this study, we showed behavioral evidence that response times decreased with the higher frequency of occurrence of the upcoming stimulus. The evidence consisted of lower response times for categories with the higher frequencies of occurrence in the input as opposed to the category with lower frequencies of occurrence. Higher probability could be reasonably more predictable and therefore facilitated classification response and reduced response times. This result could be explained if the response to each category engaged anticipatory processes that completed with the overall probability information across all categories. The results were in line with our hypothesis that the anticipatory representation acquired through distributional learning affects responses in a classification task by allowing faster response times according to the frequency of a category appearing.

Previous studies have been focused on frequency information learning between specific stimulus-stimulus associations (e.g. Conway et al. 2005; Kirkham et al. 2002; O'Brien & Raymond, 2012; Olson & Chun, 2001; Turk-Browne et al. 2005). However, no study, to our knowledge, has looked into the effect on distributional information about the internal representations of the stimuli. And here we present robust evidence that implicit distributional information about the internal representations of the stimuli could be learned, subsequently facilitated responses to trials of the more frequent category, and therefore caused the anticipation effect.

We also found that participants could learn new distributional information and this new information could override the previously learned distribution relatively quickly (i.e., within 30 trials or one block of the experiment). Although our finding gives a rather coarse estimate of distributional learning efficiency due to the use of response times as an index of learning with relatively low resolution, this result provides strong evidence for on-line learning, because the participants were required to give a response on every trial. Some previous studies relied on off-line learning tests so that they have not been able to study the speed of the distributional learning. Other studies that looked into the on-line learning of probabilistic information also suggested that probabilistic information could be obtained quickly (Abla, Katahira, & Okanoya, 2008; Turk-Browne et al., 2009), although these studies used probabilistic information about stimulus-stimulus associations instead of the overall distributional pattern of the stimuli.

Additionally, results showed that building and tool categories were less affected by frequency than faces were. Humans are highly experienced at recognizing faces for evolutionary purposes (Leopold & Rhodes, 2010; Little, Jones, & DeBruine, 2010; Sheehan & Nachman, 2014), and therefore it is possible that human faces can be more quickly recognized and distinguished than other categories can. The perception of faces might have a lower minimal response time in the high-frequency condition, and thus participants' performance for faces was far faster than the other conditions at the 60% frequency.

At the beginning of the paper, we intended to measure the anticipation of the probabilistically distributed category using comparisons between response times. The above results, using response times as the indication of the anticipation effect, showed that the participants successfully learned and used the distributional information. However, although response time has been used in some studies as an indication of anticipation (Haith et al., 1988; Hinrichs et al., 1970; Todorovic et al., 2011; Poulton, 1950), it does not directly measure the neural response to anticipatory effect after distributional learning. It is possible that the categories were also directly encoded or primed at relative magnitudes in the brain as a function of frequency, producing this response time effect. This promising result from this behavioral experiment points to the possibility of a future experiment using neuroimaging techniques (e.g., fMRI) to test the hypothesis that probabilistically weighted brain activity also corresponds to the category frequencies, and can be found in the neural activity immediately prior to each trial.

Further studies can combine our behavioral results with the ability to detect categorical specific activation using fMRI to explore the neural basis of anticipation after implicit distributional learning. The adaptive nature of human categorization assumes that categorization reflects the optimal estimates of the probability of unseen features of objects (Anderson & Milson, 1989). Turk-Browne et al. (2010) identified a neural mediator of anticipation for stimuli as a consequence of implicit distributional learning of paired and unpaired images using fMRI. A region of interest analysis of this study found increased activation of the category-specific brain area from the anticipation of that category and suppressed activation of the area when the predictive stimulus was from another category. These findings suggest that category-specific cortical activation due to implicit perceptual anticipation after implicit probabilistic learning is detectable in the category-specific brain regions using fMRI.

In sum, our study gave behavioral evidence that anticipation for the category of the upcoming stimulus is proportional to the distribution over all the categories. In the future, we hope to see neuroimaging experiment that shows anticipation after distributional learning can be measured in brain activity, and the representation is proportional to the learned distribution.

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