Vision Research 148 (2018) 37–48

Contents lists available at ScienceDirect

Vision Research

journal homepage: www.elsevier.com/locate/visres

Unsupervised visual discrimination learning of complex stimuli: Accuracy, bias and generalization

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ARTICLE INFO

Number of reviewers = 2

Keywords:
Discrimination learning
Visual discrimination
Unsupervised learning
Same-different
Bias
Generalization

ABSTRACT

Through same-different judgements, we can discriminate an immense variety of stimuli and consequently, they are critical in our everyday interaction with the environment. The quality of the judgements depends on familiarity with stimuli. A way to improve the discrimination is through learning, but to this day, we lack direct evidence of how learning shapes the same-different judgments with complex stimuli. We studied unsupervised visual discrimination learning in 42 participants, as they performed same-different judgments with two types of unfamiliar complex stimuli in the absence of labeling or individuation. Across nine daily training sessions with equiprobable same and different stimuli pairs, participants increased the sensitivity and the criterion by reducing the errors with both same and different pairs. With practice, there was a superior performance for different pairs and a bias for *different* response. To evaluate the process underlying this bias, we manipulated the proportion of same and different pairs, which resulted in an additional proportion-induced bias, suggesting that the bias observed with equal proportions was a stimulus processing bias. Overall, these results suggest that unsupervised discrimination learning occurs through changes in the stimulus processing that increase the sensory evidence and/or the precision of the working memory. Finally, the acquired discrimination ability was fully transferred to novel exemplars of the practiced stimuli category, in agreement with the acquisition of a category specific perceptual expertise.

1. Introduction

Humans can discriminate an immense variety of sensory stimuli, ranging from highly dissimilar to highly similar exemplars. Although stimuli that differ in simple features are easily distinguishable, the discrimination of highly similar stimuli can be difficult or even unattainable. Visual sensory judgements are improved with practice up to "expert" levels of discrimination. Indeed, trained observers are able to rapidly distinguish subtle differences between stimuli or identify specific patterns, for example X-Rays (Boutis, Pecaric, Seeto, & Pusic, 2010) or cytopathological images (Crowley, Naus, Stewart, & Friedman, 2003; Evered, Walker, Watt, & Perham, 2013). In natural conditions, humans learn to discriminate complex visual stimuli through their daily experience in an unsupervised manner (Saffran & Kirkham, 2017). However, the majority of studies that have characterized visual learning in supervised conditions included explicit labels or/and feedback on performance, but see Tian and Grill-Spector (2015).

Sensory judgements are typically evaluated by the Signal Detection Theory (SDT) that distinguishes two independent components: the sensitivity and the criterion (Green & Swets, 1966). Usually, the effects of experimental manipulations on the sensitivity are attributed to changes in the perceptual process and the effect on the criterion to a decisional process. Interestingly, the manipulation of perceptual aspects of the task can have an effect on the criterion in certain conditions (Witt, Taylor, Sugovic, & Wixted, 2015). Thus, the effects on the perceptual processing are not exclusively associated to changes in the sensitivity as previously assumed. Alternatively, the performance has been evaluated in a model-free mode by the percentage of correct responses and the response preference that provides a measure of the predisposition to select among the response options.

The better performance of experts on discrimination of complex stimuli, measured as increases in sensitivity or accuracy, is attributed to

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https://doi.org/10.1016/j.visres.2018.05.002
Received 11 January 2018; Received in revised form 1 May 2018; Accepted 4 May 2018
Available online 25 May 2018
0042-6989/

the acquisition of a domain specific ability. A characteristic of the expert's discrimination is its generalization to the whole stimuli category. Moreover, the acquisition of this ability requires stimulus naming or categorization at the subordinate level and feedback on performance (Scott, Tanaka, Sheinberg, & Curran, 2006; Scott, Tanaka, Sheinberg, & Curran, 2008; Tanaka, Curran, & Sheinberg, 2005; Wong, Palmeri, & Gauthier, 2009), which together is defined as supervised experience or training. Alternatively, expert discrimination was obtained by the unsupervised identity training without labeling (Bukach, Kinka, & Gauthier, 2012) and a greater sensitivity and reduced incorrect responses to same and different pairs were obtained by unsupervised exposure to 3D stimuli (Tian & Grill-Spector, 2015). These results suggest that unsupervised training with stimulus individuation can lead to expert's levels of performance. In contrast, the unsupervised exposure to car models did not improve the sensitivity (Scott et al., 2008) suggesting that mere exposure is not sufficient for visual discrimination learning.

In addition to the sensitivity effects, visual learning may shift the criterion, typically associated to a decisional instead of perceptual process. A few studies have described contrasting results of criterion shifts. For example, unsupervised learning in a contrast discrimination and detection task with Gabor patches resulted in a shift in the criterion towards liberal values (Wenger, Copeland, Bittner, & Thomas, 2008; Wenger & Rasche, 2006). On the contrary, supervised discrimination learning in an auditory detection task reduced a bias in the criterion found in naïve observers (Jones, Moore, Shub, & Amitay, 2015). These contradictory results on criterion shifts may arise from differences in the feedback provided. Although feedback appears to be necessary for learning in perceptual tasks (Herzog & Fahle, 1997), it can also modify the sensitivity when provided block-wise (Aberg & Herzog, 2012) or induce a change in the criterion if observers receive a biased feedback (Herzog & Fahle, 1999). Accordingly, the feedback on performance may induce a response bias. Alternatively, a perceptual bias may induce criterion shifts (Witt et al., 2015). In consequence, the improvements in sensory judgements may involve shifts in the criterion with the consequent bias, in addition to improvements in sensitivity.

Same-different judgments are fundamental processes that take place during perceptual discrimination (Farell, 1985; Melara, 1992) and do not require a predefined feature or criterion for discrimination. The use of same-different tasks to compare the discrimination of naïve and expert observers has shown a reliably greater sensitivity for human movements in expert dancers (Calvo-Merino, Ehrenberg, Leung, & Haggard, 2010) and for cars models in car experts (Bukach, Phillips, & Gauthier, 2010). Supervised visual training with stimulus naming and categorization at the subordinate level, resulted in an improvement of sensitivity for birds (Tanaka et al., 2005) and car models (Scott et al., 2008). Because these studies were concerned with the modifications in the accuracy and sensitivity of experts, there were no explicit measures of accuracy for same and different trials individually or response bias. However, early perceptual studies with familiar stimuli showed a bias, characterized by more error with same pairs, in pitch discrimination (Coltheart & Curthoys, 1968) and simultaneous or sequential letter discrimination (Proctor & Rao, 1983). In contrast, no bias in the accuracy for same and different pairs was observed in the discrimination of sequential multi-letter pairs (Proctor, Rao, & Hurst, 1984). Additional studies of same-different judgements showed no bias on the accuracy for same and different pairs with familiar stimuli (flowers or human faces, accuracy > 0.9, Gauthier, Behrmann, & Tarr, 2004). However, a bias based on more errors on same pairs, was obtained with unfamiliar pseudo-Chinese characters (Chen, Bukach, & Wong, 2013). Moreover, supervised exposure to random viewpoints of unfamiliar 3D images resulted in a lower reduction of errors on "same" stimuli pairs (Tian & Grill-Spector, 2015), in agreement with a differential effect of training for same and different pairs. Overall, these results suggest that different levels of familiarity with the stimuli may modulate the relative errors on same and different pairs, and thus the occurrence of a bias in the response.

In conclusion, there is not enough evidence to demonstrate that visual discrimination learning equivalent to "expert" levels can be attained through same-different judgements of stimuli pairs in an unsupervised manner and how increasing grades of familiarity with stimulus patterns shape the performance for same and different pairs and the contribution of a bias in the criterion. To address this issue, we used a modified version of the same-different task where participants learned to discriminate complex visual stimuli in unsupervised conditions. In this study, we characterized the visual discrimination learning of two unfamiliar complex multi-exemplar stimuli categories. We evaluated if perceptual training was accompanied by shifts in criterion and response preference in addition to the increase in sensitivity and accuracy for same-different stimuli pairs while the observers acquired familiarity with the stimuli category. Moreover, we evaluated if perceptual training led to a generalization of the acquired discrimination abilities in agreement with perceptual expertise acquisition. In the first experiment, participants performed the same-different judgments with an equal number of same and different pairs, kanji or checkerboards, across nine daily sessions. We evaluated the effect of practice on performance and the specificity of learning for the stimuli category. In the second experiment, we manipulated the proportions of same and different pairs to induce a response bias (Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012) and test if this manipulation reduced or eliminated the bias in the response observed in the first experiment. Two different groups of participants learned to discriminate unequal and inverse proportions of same and different checkerboard pairs of which they had no prior information, across five daily sessions. In the present work, we were interested in the processes of unsupervised experience-dependent visual discrimination learning. Thus, participants performed the task without either trial- or block-based feedback on performance.

2. General methods

2.1. Participants

Adults with normal or corrected to normal vision were recruited through advertisements placed around the Medical School at the University of Chile and received a monetary compensation (approximately 40 US$ dollars). Experiments were conducted in accordance with Protocol #031-2008 approved by the Ethical Committee of the Medical School in the University of Chile in agreement with the Code of Ethics of the World Medical Association (Declaration of Helsinki). All participants gave written informed consent.

2.2. Stimuli

Two types of black and white stimuli, kanji characters (45 exemplars, 17 and 18 strokes), and scrambled checkerboard-like patterns (45 exemplars, 10×10 squares) were selected. Both stimuli were previously used in visual studies (Chen et al., 2013; Civile et al., 2014). Participants had no prior experience with either stimuli as specified in the recruiting interview. Checkerboards were designed with similar average luminance to kanji stimuli, calculated as the mean number of white pixels in the image. Stimuli (1×1 visual degrees) were presented over a black background at the center of the screen, at a distance of 57 cm from the eyes in a CTR 19 in. monitor (Samsung SyncMaster 1100P Plus, refresh rate of 120 Hz), with the software Experiment Builder (v1.6.121, SR Research Ltd., Mississauga, Canada) or in a LCD 20.1 in. monitor (Dell E207WFPc, refresh rate 60 Hz), with NI Labwindows CVI (Austin, Texas, USA).

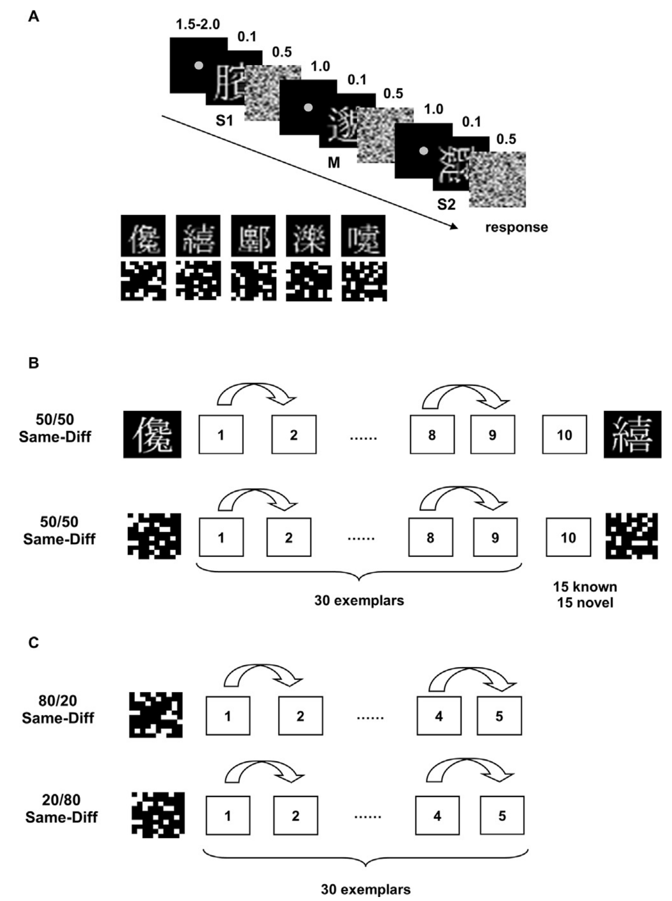

Fig. 1. Trial sequence and experimental protocols. A. An example of a same-different trial consisting of the sequence of images: stimulus 1 (S1), perceptual mask (M) and stimulus 2 (S2), all followed by a noise image and five exemplars of the two stimuli categories. B. Protocol for the practice sessions (1–9) and the evaluation session (10) of experiment 1. C. Protocol applied in the practice sessions (1–5) of experiment 2. http://dx.doi.org/10.17504/protocols.io.h5ub86w.

3. Experiment 1. Unsupervised same-different practice with an equal proportions of stimuli is sufficient for discrimination learning and generalization

The aim of this experiment was to examine the properties of unsupervised visual discrimination learning based on the sensory experience acquired through practice of same-different judgements. Specifically, we evaluated (1) if the improvements in sensitivity and accuracy were accompanied by changes in the criterion and the emergence of a bias in the response, respectively and (2) the generalization of the acquired discrimination ability to new exemplars of the practiced category.

3.1. Method

Twenty right handed college students and professors ages 18–48 participated in this experiment. All participants received detailed information about the experimental sequence before the behavioral sessions. Participants were seated in a dimly lit room with reduced noise. Each trial (Fig. 1A) began with a fixation dot (1.5–2.0 s), followed by a sequence of two stimuli, S1 and S2 (0.1 s each) and a perceptual mask M (0.1 s) between S1 and S2. The perceptual mask, consisting of a single image of the same category and different from S1 and S2, was introduced to reduce the priming effect of S1 on S2 for same pairs. S1 and M were followed by a white noise image (0.5 s) and S2 was followed by a white noise image (5 s). The fixation dot was present (1 s) between the noise image and the succeeding M or S2 images to facilitate the eye fixation at the center of the screen. Participants began each trial by pressing a button to reduce the effect of variable attention on the first stimulus. After the presentation of S2, the participants had to respond, by pressing one of two buttons, if the stimuli pair was perceived as *same* or *different*. Half of the participants responded *same* with the right hand and the other half with the left hand. They were instructed to respond as accurately and as fast as possible. To avoid the discrimination based on the retinal matching of S1 and S2 on same pairs and to promote object discrimination, S2 was rotated 90 degrees clockwise or counter-clockwise in a pseudo-random manner (Tian & Grill-Spector, 2015). Participants were informed that the third stimulus was rotated.

Because the aim of this work was to characterize discrimination learning in unsupervised conditions, participants performed the task in the absence of stimulus labeling and without feedback on performance to minimize the effect of feedback on sensitivity (Aberg & Herzog, 2012) and criterion (Herzog & Fahle, 1999). Participants were assigned to two groups in a random manner, one group (n = 10) performed the task with kanji and a different group (n = 10) with checkerboard stimuli (Fig. 1B). The experiment consisted of nine daily practice sessions and an evaluation session, each lasting on average 1 h. For the practice sessions, we built ten stimuli lists with the same set of 30 exemplars, consisting of a random sequence of same and different pairs with an equal frequency of each exemplar as S1, S2 and M. The list was randomly selected for each participant. In the evaluation session, participants performed the task with a set of 15 exemplars of those used in the practice sessions (practice set) and the 15 remaining exemplars not presented during the practice sessions (novel set). Each pair of stimuli was from either the practiced set or the novel set. We built ten evaluation lists with a randomized order of pairs with an equal frequency of the exemplars as S1, S2 and M. All sessions had an equal number of same and different pairs (50/50). Participants were informed of the equal proportions the first session. Sessions consisted of 480 trials, divided into 8 blocks of 60 trials. Between blocks, participants were free to rest and received food and/or beverages upon request.

Because there was no feedback on performance, we anticipated a high variability in their attention and motivation. To promote motivation and attention, each participant's performance was evaluated at the end of each session and if there was no increase in performance in two successive sessions, participants were told verbally that they should make an effort to be more attentive and perform better during the task. No quantitative information regarding correct or incorrect responses was provided. Moreover, all participants were encouraged to perform well at the beginning of each session.

3.2. Data processing

The performance in a same-different task relies on stimuli discrimination and response selection. In the signal detection theory, stimuli discrimination is quantified as the discrimination index (d prime, d') or sensitivity, and the response selection is quantified by the criterion. The sensitivity is an indicator of the participant's ability to detect a signal in the presence of noise (Green & Swets, 1966) and with the proper corrections; it can be applied to same-different tasks (Sorkin, 1962). With several exemplars, an observer assumes the differencing strategy, where the decision is based on the absolute difference between stimuli (Macmillan & Creelman, 2005). Thus, sensitivity and criterion were calculated with the differencing model, using the Palamedes toolbox (www.palamedestoolbox.org, PAL_SDT_1AFCsameDiff_DiffMod_PHFtoDP routine, Kingdom & Prins, 2010) written in Matlab (The MathWorks Inc.) according to the following equations:

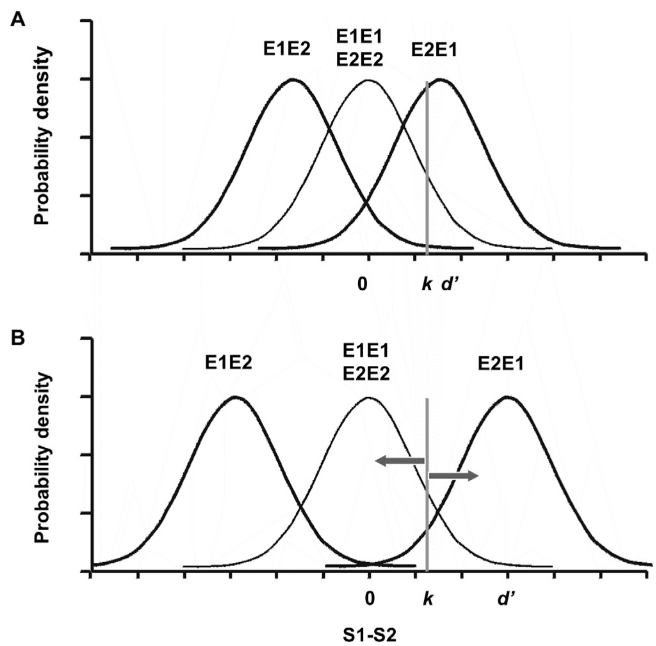

Fig. 2. Scheme of the decision space for the differencing model before and after discrimination learning. A. Scheme of the probability density distributions as a function of the difference between stimuli 1 and 2 (S1-S2) before discrimination learning. Same pairs of exemplars 1 and 2 (E1E1, E2E2) are represented by the middle distribution and of different pairs (E1E2, E2E1) by the right- and left-hand side distributions. D prime (*d'*) and the criterion (*k* vertical gray line) are shown in the x axis. B. Scheme of the probability density distributions after discrimination learning. An increase in *d'* and the possible outcomes of the criterion (*k*) are shown. An increase in criterion is represented by the right arrow and a decrease by the left arrow.

$$pH = \Phi[(d'-k)/\sqrt{2}] + \Phi[(-d'-k)/\sqrt{2}]$$
$$pFA = 2\Phi(-k/\sqrt{2}) \quad (1)$$

where pH is the probability of a *different* response to different pairs, pFA is the probability of a *different* response to same pairs, ϕ the cumulative probability, *d'* the sensitivity and *k* the criterion. The criterion (*k*) values correspond to the minimum difference between stimuli being classified as *different*. The *k* values are all positive and a *k* equal to 1 corresponds to a pFA of 0.5. A scheme of the differencing model before and after discrimination learning is shown in Fig. 2, where *d'* and *k* are shown only on the right side for simplicity. Here, the probability density function for the pairs formed by exemplars 1 (E1) and 2 (E2) are shown as a function of the difference between first and second stimulus (S1, S2). Same pairs (E1E1, E2E2) are represented by the middle distribution and the different pairs by the left (E1E2) and right (E2E1) distributions. Before discrimination learning (Fig. 2A), there is overlap of the same and different distributions. The vertical grey line represents the criterion (*k*), whereas the pHits are represented by the area to the right of *k* in the right hand distribution and pFA are represented by the area to the right of *k* in the central distribution.

After discrimination learning (Fig. 2B), there is a reduction in the overlap of the central and right- and left-hand distributions corresponding to an increase in *d'*. The criterion may: 1) decrease (left grey arrow) corresponding to a reduction in the minimum difference between the stimuli classified as *different*, 2) increase (right grey arrow), corresponding to an increase in the minimum difference between the stimuli classified as *different*, or 3) remain unchanged (vertical gray line). The observers in a same-different task may adopt the strategy of a constant criterion (*k*) with a shift in the likelihood ratio of same and different events as accuracy increases, of a constant likelihood ratio with a shift of the criterion values as the accuracy increases or an adjustment of both criterion and likelihood.

The accuracy for same (or different) pairs estimated as the percentage of correct *same* (or *different*) responses was calculated as the number of correct *same* (or *different*) responses divided by the total number of same (or different) pairs multiplied by 100. We calculated the response preference as the number of *same* responses divided by the total responses multiplied by 2. This index is *1.0* when the participant's responses are equally distributed between the *same* and *different* options, greater than 1.0 when *same* responses exceed *different* responses and smaller than 1.0 when *different* responses exceed *same* responses.

3.3. Statistical analysis

Statistical differences in sensitivity, criterion and response preference were evaluated with a repeated measures two factor analysis of variance (ANOVA) with between-subject factors of stimulus type (two levels, kanji and checkerboards) and within-subject factor of practice (nine levels, sessions 1 through 9. The differences in the percentage of correct responses were evaluated with a repeated measures two factor ANOVA with within-subject factors of stimuli pair (two levels, same and different) and practice (nine levels, sessions 1 through 9). F values were corrected using Greenhouse-Geisser for significant Mauchly s sphericity test values. Significance values were set at $p < 0.05$. Differences between means were assessed with t-tests and differences between a mean and a fixed value were evaluated by a one-sample *t*-test. T-tests alpha values were adjusted for multiple comparisons using Bonferroni correction (0.05/number of comparisons). All tests were done using SPSS (16.0. Chicago, SPSS Inc.). Unless otherwise specified, all values are reported as mean + SD from the mean. Data from each participant are shown in the supplementary figures (SF).

3.4. Results

We evaluated the accuracy and bias during unsupervised discrimination learning and its generalization to the practiced stimuli category. Participants learned to discriminate an equal proportion of same-different (50/50) pairs. First, we show a shift in criterion in addition to the improvements in sensitivity across sessions, along with the increase in accuracy and the emergence of a bias in the response. Lastly, we show that the unsupervised learning generalizes to novel exemplars of the practiced category.

3.4.1. Sensitivity

Each participant's sensitivity was estimated for each session. There was an approximately two fold increase in *d'* between the first and ninth sessions for both kanji and checkerboard stimuli (Fig. 3A and supplementary Figs. 1 and 2, SF1, SF2). With kanji stimuli, *d'* increased from M = 1.84, SD = 0.72 in the first to M = 3.68, SD = 0.87 in the ninth session. Likewise, with checkerboard stimuli *d'* increased from M = 1.67, SD = 0.83 in the first to M = 3.83, SD = 0.50 in the ninth session.

A 2×9 repeated measures ANOVA (stimulus type x session number) showed an unsurprising main effect of session number ($F(3.79, 68.3) = 64.2$, $p < .001$, $\eta_p^2 = 0.781$), no effect of stimulus type ($F(1, 18) = 0.012$, $p = .915$, $\eta_p^2 = 0.001$) and no interaction between stimulus type and session number ($F(3.794, 68.293) = 0.859$, $p = .488$, $\eta_p^2 = 0.046$). Pairwise comparisons between the first and succeeding sessions confirmed an increase in *d'* beginning with the second session ($p < .001$, alpha = 0.05/8 test = 0.00625). In summary, unsupervised practice of same-different judgements with unfamiliar stimuli resulted in a similar improvement in visual discrimination with both kanji and checkerboards categories

3.4.2. Criterion

The criterion (*k*) exhibits about a 35% increase with practice for both kanji and checkerboard stimuli (Fig. 3B and SF3 and SF4). With kanji, *k* increased from M = 1.37, SD = 0.29 in the first to M = 1.87,

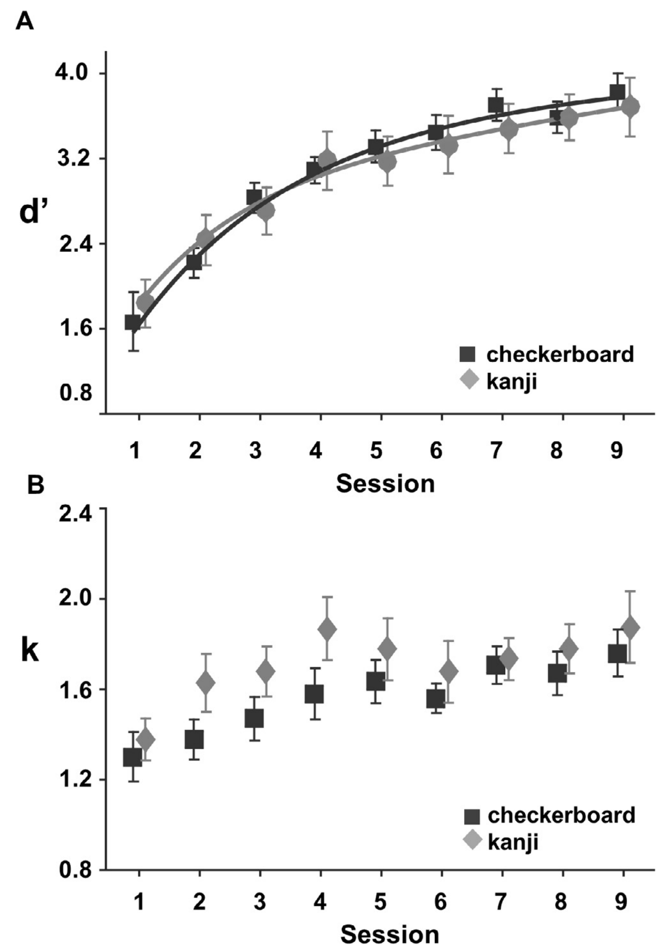

Fig. 3. Unsupervised discrimination practice increased the sensitivity and the criterion. A. *d'* during practice sessions for kanji (grey) and checkerboard (black) stimuli. B. Criterion (*k*) as a function of practice sessions for kanji and checkerboards stimuli. Error bars are SE of the mean.

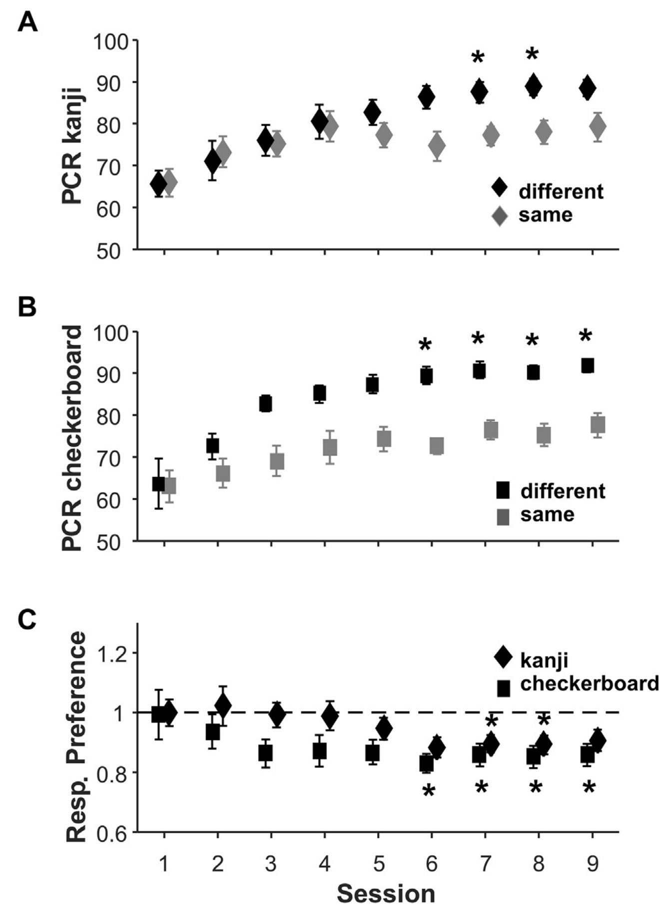

Fig. 4. Unsupervised discrimination practice increased the accuracy and a change in the response preference. A. Percentage of correct responses (PCR) for same (gray diamond) and different (black diamond) kanji pairs during discrimination practice. B. Percentage of correct responses for same (grey square) and different (black square) checkerboards pairs during discrimination practice. C. Response preference for kanji (diamond) and checkerboards (square) stimuli. Asterisks indicate statistical differences between pair types and stimuli types (*, $p < .01$). Error bars are SE of the mean.

SD = 0.50 to the ninth session, corresponding to a reduction from 0.33 to 0.19 in the fraction of "same" pairs classified as *different*, respectively. Likewise, with checkerboards *k* increased from M = 1.30, SD = 0.35 in the first to M = 1.76, SD = 0.33 in the ninth session, corresponding to a reduction from 0.36 to 0.21 in the fraction of "same" pairs classified as *different*, respectively. The ANOVA indicated a main effect of session number ($F(3.17, 57.0) = 7.00$, $p < .001$, $\eta_p^2 = 0.280$), no effect of stimulus type ($F(1, 18) = 1.64$, $p = .217$, $\eta_p^2 = 0.083$) and no interaction between session number and stimulus type ($F(3.17, 57.0) = 0.582$, $p = .638$, $\eta_p^2 = 0.031$). Pairwise comparisons of the criterion between the first and succeeding sessions revealed an increase in the criterion beginning at the fourth session ($p \leq .003$, alpha = 0.00625), with the exception of the sixth session ($p = .018$). In summary, unsupervised practice resulted in a similar increase in the criterion for both kanji and checkerboard categories.

3.4.3. Accuracy

The increase in the sensitivity and criterion are consistent with an increase in correct responses for both same and different pairs across sessions. To further examine this effect, we estimated the percentage of correct responses for same and different pairs individually, and the response preference. As expected, task practice with kanji and checkerboard stimuli resulted in increases in accuracy for same and different pairs (Fig. 4 and SF5 and SF6). Surprisingly, the increase in the accuracy was greater for different pairs with both kanji and checkerboards.

With kanji, the accuracy for same pairs increased from M = 0.66, SD = 0.10 in the first to M = 0.79, SD = 0.11 in the ninth session and the accuracy for different pairs increased from M = 0.66, SD = 0.10 in the first to M = 0.88, SD = 0.06 in the ninth session (Fig. 4A and SF5). A two factor repeated measures ANOVA (session number and pair type) showed a main effect of session number ($F(3.13, 28.1) = 21.4$, $p < .001$, $\eta_p^2 = 0.704$), no effect of pair type ($F(1, 9) = 2.59$, $p = .142$, $\eta_p^2 = 0.223$), and an interaction between session number and pair type ($F(2.36, 21.2) = 3.59$, $p = .039$, $\eta_p^2 = 0.285$). Pairwise comparisons of the correct responses between the first and succeeding sessions revealed an increase from the second session ($p \leq .001$, alpha = 0.05/8 = .00625). Pairwise comparison of accuracy between same and different pairs from the second to the ninth sessions revealed a marginally greater accuracy with different pairs in sessions seventh ($p = .0064$, alpha = 0.00625) and eight ($p = .0061$). Thus, unsupervised learning resulted from both, an increase in correct responses for both same and different pairs and a greater accuracy for different pairs with greater levels of familiarity with the stimuli.

With checkerboards, the accuracy for same pairs increased from M = 0.63, SD = 0.12 in the first to M = 0.78, SD = 0.09 in the ninth session, and the accuracy for different pairs increased from M = 0.63, SD = 0.19 in the first to M = 0.92, SD = 0.05 in the ninth session (Fig. 4B and S6). The ANOVA indicated a main effect of session number ($F(8, 72) = 31.8$, $p < .001$, $\eta_p^2 = 0.779$) and pair type ($F(1, 9) = 11.7$, $p = .008$, $\eta_p^2 = 0.565$) but no interaction between pair type and session number (F (1.83, 16.5) = 1.83, p = .193, ηp^2 = 0.217). Pairwise comparisons of accuracy between the first and succeeding sessions revealed a significant increase of performance from the fifth session ($p \leq$ .004, alpha = .00625). Pairwise comparison of accuracy between same and different pairs from the second to the ninth sessions revealed a greater accuracy with different pairs in sessions six through nine ($p \leq$ .005, alpha = .00625). Thus, unsupervised learning resulted from both, an increase in corrected responses for same and different pairs and an effect or pair type indicated by the greater performance of different pairs in the last sessions.

Taken together, these results indicate that unsupervised practice improved the discrimination of same and different pairs for both kanji and checkerboards, with a greater accuracy for different pairs in the last sessions, suggesting the emergence of a bias the in response selection.

3.4.4. Response bias

Does the greater performance with different pairs reflect a bias in the response? As illustrated in Fig. 4C and SF7, there was a small but significant decrease in the response preference across sessions. With kanji, the response preference decreased from M = 1.00, SD = 0.14 in the first to M = 0.91, SD = 0.11 in the ninth session. Likewise, with checkerboards the response preference decreased from M = 0.99, SD = 0.26 in the first to M = 0.86, SD = 0.12 in the ninth session. As expected, the ANOVA resulted in a main effect of session number (F (2.34, 42.2) = 4.26, p = 0.016, η_p^2 = 0.191), no effect of stimulus type (F (1, 18) = 1.95, p = .179, η_p^2 = 0.098) and no interaction between session number and stimulus type (F (2.34, 42.2) = 0.706, p = .521, η_p^2 = 0.038). The response preference decreased from the first to the nine session (p = .046, paired *t*-test). Moreover, a one sample *t*-test of the response preference with respect to the value of an unbiased observer (1.0) was no different in sessions second to fifth and ninth ($p \geq$ .008, alpha = 0.05/8 tests = 0.0065) but smaller than 1.0 in the seventh and eight sessions ($p \leq$ .006) with kanji. Likewise, with checkerboards the response preference was not different from 1.0 in the second to fifth sessions ($p \geq$ .012, alpha = 0.006) but was smaller than 1.0 from the sixth through ninth sessions ($p \leq$ .005, alpha = 0.006). These results suggest that discrimination practice resulted in a bias in the response selection in agreement with the greater performance for different pairs in the last sessions.

3.4.5. Exemplar and category specific discrimination learning

A distinctive feature of expert performance is generalization of the domain specific ability within the trained category (Tanaka et al., 2005). Thus, we evaluated how much of the visual learning is generalized to novel exemplars of the trained category. Thus, the kanji and checkerboard groups performed same-different judgements with a randomized sequence of pairs of practiced exemplars and pairs of novel exemplars of the practiced category on the tenth session. The mean *d*' with novel pairs was slightly smaller than *d*' for practiced pairs for both checkerboards and kanji stimuli (Fig. 5). D-prime exhibited a small decreased from M = 3.89, SD = 1.10 for practiced kanji to M = 3.49, SD = 0.96 for novel kanji pairs (p = .023, alpha = 0.05, Fig. 5A), but was similar (p = .256) with practiced checkerboards (M = 4.02, SD = 0.62) and novel checkerboards (M = 3.78, SD = 0.69, Fig. 5B), denoting a nearly full generalization of the learning. Moreover, the sensitivity with novel exemplars was greater than the sensitivity of naïve participants in the first session for both stimuli (M = 1.84, SD = 0.72, p < .001 and M = 1.67, SD = 0.83, p < .001) for kanji and checkerboards respectively. To sum up, these results show a nearly complete generalization of the acquired discrimination learning to novel exemplars of the practiced category.

3.5. Discussion of experiment 1

We examined the performance while participants learned to discriminate complex visual stimuli in unsupervised conditions. We evaluated the modifications on the criterion and response preference in addition to the sensitivity and accuracy for two types of unfamiliar multi-exemplar stimuli and the generalization of learning to novel exemplars of the trained category. The main findings of this experiment were that 1) practice of same-different judgments in unsupervised conditions leads to discrimination learning based on shifts in the criterion and the emergence of a bias in addition to the increase in the discriminability and 2) this learning generalizes to novel exemplars of the trained category.

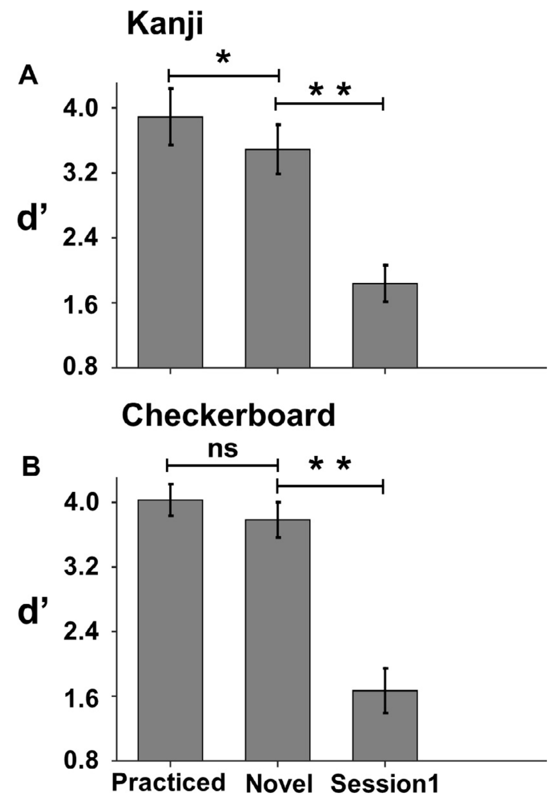

Fig. 5. Generalization of learning to novel exemplars of the practiced category. A. *d'* with practiced and novel kanji exemplars in the evaluation session and in the first practice session. B. *d'* with practiced and novel checkerboard exemplars in the evaluation and the first practice session, (*, p < .05; **, p < .001; ns, non-significant). Error bars are SE of the mean.

Specifically, our results show that unsupervised practice with an equiprobable fraction of same and different pairs results in a significant enhancement in the discriminability regardless of the stimulus type (Fig. 3). Our results are consistent with previous findings of supervised training for several stimuli types (reviewed by Fine & Jacobs, 2002; Op de Beeck, Baker, Dicarlo, & Kanwisher, 2006; Wong, Folstein, & Gauthier, 2011) and of unsupervised training with artificial 3D stimuli (Tian & Grill-Spector, 2015). Thus, our results confirm that extended practice of visual comparisons in the absence of stimulus labeling and feedback on performance were sufficient to attain significant visual discrimination learning.

In addition to the effect of practice on sensitivity, there was a small but significant shift in the criterion for both types of stimulus (Fig. 3). The criterion index k is proportional to the z transform of false alarms (see methods), a response *different* to same pairs. Thus, an increase in k reflects a reduction of the same pairs classified as *different* and that the minimum difference between the stimuli classified as *different* increased as accuracy increased (Fig. 2). Our results are consistent with previous shifts of the criterion in unsupervised learning (Wenger & Rasche, 2006; Wenger et al., 2008). A shift in the criterion is typically attributed to modifications in the decision criterion that takes place after the acquisition of the sensory evidence. Thus, our results suggest that discrimination practice modify the decision criterion.

To better characterize the modification of the criterion, we used a model-free approach to assess the performance of same-different pairs individually. Our results show an important increase in the accuracy with discrimination practice indicated by the robust effect size of session number for both stimuli, kanji and checkerboards. Moreover, the performance of same and different pairs individually was dependent on the extent of practice for kanji and checkerboards. The post hoc tests show a marginal difference in the last sessions for kanji but a significant difference for checkerboards. Although, the differences in the performance with same and different pairs for kanji and checkerboards have a low power due to the small number of participants in each group, the consistency of the results with both stimuli categories represent a replication and thus, a validation of the better performance with different stimuli pairs. Additional studies should be done to confirm the effect of practice on the discrimination of same and different pairs. In general, the majority of studies on visual perceptual studies have focused on the changes in sensitivity and the overall performance, without examining the accuracy for same and different pairs individually. Nonetheless, a few studies showed a distinct performance for same and different pairs described in supervised and unsupervised perceptual studies (Aly & Yonelinas, 2012; Chen et al., 2013; Krueger, 1978; Proctor & Rao, 1983). A recent study described an equal decrease in errors for same and different pairs in unsupervised training with 3 D artificial images (Tian & Grill-Spector, 2015), although the absolute accuracy levels were not reported. In conclusion, we found a distinct effect of discrimination training on the accuracy for same and different pairs in unsupervised conditions.

The criterion shift and the superior performance for different pairs are consistent with the emergence of a bias in the response selection (Fig. 4). Thus, these results suggest that response preference is modulated by the observer's familiarity with the stimuli. On average, naïve observers showed no bias, although there was a greater variability in the individual responses (SF 7). After the accumulation of sensory evidence with task practice, a bias in the response preference emerged. Again, the main effect of training on response preference was marginally significant in the pairwise comparisons for kanji and significant for checkerboards, likely due to the low number of participants. Nonetheless, the replication of the effect with both stimuli support the effect of training on response preference.

In conclusion, our results show that the discrimination learning does not require stimulus labeling and feedback on performance. More importantly, that discrimination practice in unsupervised conditions improves stimuli discriminability and modifies the decision criterion revealing a bias in the response selection.

3.5.1. Generalization of learning

Here we show that the unsupervised learning generalized to pairs of novel exemplars, in agreement with a category specific processing ability and a small contribution of explicit memory for the practiced exemplars (Fig. 5). The generalization of the learning to new exemplars and categories has been examined for different stimulus types in a variety of tasks and overall, the results show different degrees of generalization. Our results are consistent with the large generalization of face view discrimination (Bi, Chen, Weng, He, & Fang, 2010) and of a "greeble" identification task (Gauthier, Williams, Tarr, & Tanaka, 1998), in agreement with a low specificity for the trained stimuli. On the contrary, our results are in contrast to the low transfer of learning observed in different tasks with different stimulus types (Baeck, Windey, & Op de Beeck, 2012; Gölcü & Gilbert, 2009; Husk, Bennett, & Sekuler, 2007; Op de Beeck et al., 2006). In summary, the extent of transfer to novel stimuli correlates with the similarity or feature sharing between the trained and the novel exemplars (Baeck et al., 2012; Gölcü & Gilbert, 2009) typical of a perceptual expertise (Bukach et al., 2010). Therefore, our results are consistent with the acquisition of perceptual expertise for complex stimuli in supervised (Gauthier & Tarr, 1997; Gauthier et al., 1998; Op de Beeck et al., 2006; Scott et al., 2008; Wong et al., 2011) and unsupervised conditions (Tian & Grill-Spector, 2015). The improvement of performance during learning likely includes stimulus specific as well as task specific abilities. In our work, several properties of the stimulus and task may have contributed to a high transfer of learning to new exemplars. Among these, the variety and similarity of exemplars and the orientation diversity (upright, 90 degrees clockwise and counter-clockwise rotation). In addition, the same-different task may have contributed by encouraging perceptual comparison of the stimuli, and restraining its labeling and individuation. Finally, task-related abilities include fast feature extraction, coding and maintenance of S1 in working memory and mental rotation of S1, all of them ought to transfer to new stimuli categories. Further studies should evaluate how much of the performance improvement is a task-related ability.

In conclusion, our results suggest that unsupervised practice of same-different discrimination with a group of representative stimuli is sufficient for the generalization of the discrimination learning in agreement with the acquisition of a perceptual expertise.

4. Experiment 2. Unsupervised same-different practice with unequal proportion of same and different stimuli

A bias in an observer's perceptual decisions can be dissociated into a perceptual bias, originated on shifts in the perceptual processing, or in a response bias, originated in beliefs or information about the stimuli proportions or rewards (Leite & Ratcliff, 2011). Specific experimental manipulations can dissociate a response bias from a perceptual bias. For instance the manipulation of the stimuli proportions can induce a response bias (Ashby, 1983). The aim of the second experiment was to test whether the bias observed in the first experiment is modified by manipulations that induce a response bias. To do so, we manipulated the proportions of same and different pairs and evaluated the performance across five practice sessions. We hypothesized that unequal and inverse proportions of stimuli would reduce or eliminate the bias in the response observed in the first experiment, in agreement with this being a response bias.

4.1. Method

Twenty-three right-handed participants age 19–24 participated in this experiment. The trial sequence was identical to that in experiment 1. We selected the checkerboards because there was an early occurrence of the superior performance with different pairs. Participants completed 5 daily practice sessions with the same set of exemplars. Each session consisted of 480 trials, divided in 8 blocks of 60 trials. Participants were assigned to two groups in a random manner; one group performed the task with a majority of same pairs, 80% same and 20% different pairs (80-same, n = 12), and another group performed the task with a majority of different pairs, 20% same and 80% different pairs (80-diff, n = 11, Fig. 1C). One participant in the 80-same group was eliminated because there was no change in performance, leaving 11 participants in the 80-same group. No feedback on performance was provided.

4.2. Data processing and statistical analysis

D prime, criterion, percentage of correct responses and response preference were calculated as in experiment1. Statistical differences in sensitivity, criterion, accuracy and response preference were evaluated as previously described for experiment 1.

Statistical differences in sensitivity, criterion and response preference were evaluated with a repeated measures two factor analysis of variance (ANOVA) with between-subject factors of stimuli ratio (two levels, 80-same and 80-diff) and within-subject factor of practice (five levels, sessions 1 through 5). The differences in the percentage of correct responses were evaluated with a repeated measures two factor

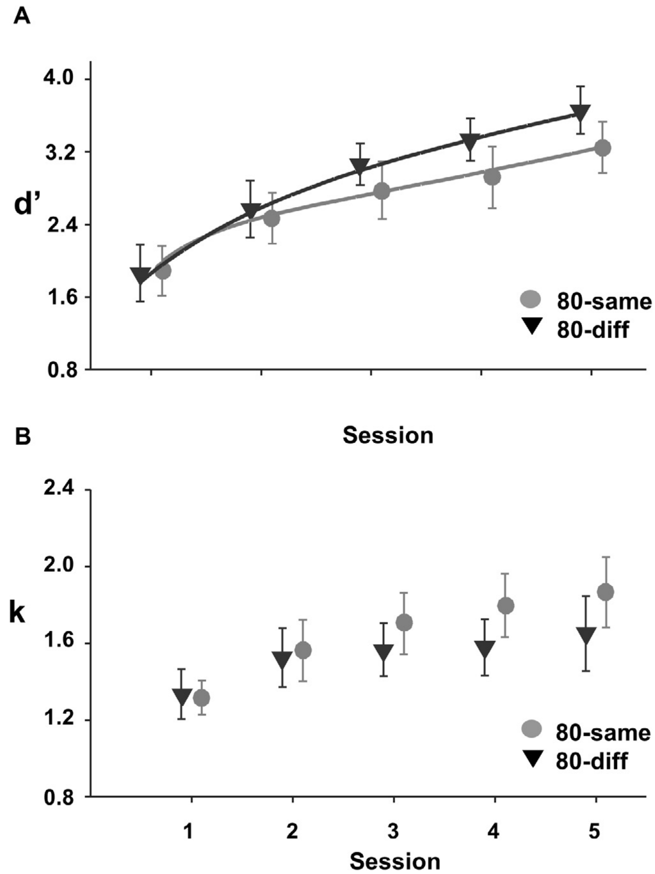

Fig. 6. Unsupervised discrimination practice with unequal and inverse proportions of stimuli. A. *d*' during practice sessions with a majority of same pairs (80-same, circle) and with a majority of different pairs (80-diff, triangle). B. Criterion (*k*) values during practice sessions for a majority of same pairs (80-same, circle) and for a majority of different pairs (80-diff, triangle). Error bars are SE of the mean.

ANOVA with within-subject factors of stimuli pair (two levels, same and different) and practice (five levels, sessions 1 through 5).

4.3. Results

In the second experiment, we evaluated if the bias of experiment 1 is modified by manipulations that induce a response bias. Thus, we manipulated the proportions of pairs and two groups of participants learned to discriminate checkerboards with unequal and inverse proportions of same and different pairs, of which the participants had no prior knowledge.

4.3.1. Sensitivity

Task practice resulted in an increase in *d*' with both 80-same and 80-diff proportions. Although there was a slightly higher *d*' for majority of different pairs in the fourth and fifth sessions (Fig. 6A and SF8), this difference was not significant. Specifically, in the 80-same group *d*' increased from M = 1.89, SD = 0.910 in the first to M = 3.25, SD = 0.940 in the fifth session and in the 80-diff group *d*' increased from M = 1.86, SD = 1.04 in the first to M = 3.66, SD = 0.869 in the fifth session. The ANOVA showed a main effect of session number (F (2.24, 44.8) = 33.0, $p < .001$, $\eta_p^2 = 0.622$), no effect of proportion (F (2.24, 44.8) = 33.0, p = .515, $\eta_p^2 = 0.021$) and no interaction between session number and proportion (F (2.24, 44.8) = 0.844, p = .448, $\eta_p^2 = 0.040$). Pairwise comparisons of *d*' means between the first and subsequent sessions indicated an increase in sensitivity from the third session ($p \leq .001$, alpha = 0.05/4 = 0.0125). In sum, practice with unequal and inverse proportions of same-different pairs resulted in better discriminability of checkerboards stimuli as observed in experiment 1.

4.3.2. Criterion

The criterion increased for both proportions (Fig. 6B and SF9). For a majority of same pairs (80-same), *k* increased from M = 1.32, SD = 0.298 in the first to M = 1.87, SD = 0.607 in the fifth session, representing a reduction in the incorrect responses to same pairs from 0.35 and 0.19, respectively. Likewise, for a majority of different pairs (80-diff) there was an increase in *k* from M = 1.34, SD = 0.433 in the first to M = 1.65, SD = 0.647 in the fifth session, representing a reduction in the incorrect responses to same pairs from 0.34 and 0.24, respectively. The ANOVA indicated a main effect of session number (F (2.56, 51.3) = 8.21, $p < 0.001$, $\eta_p^2 = 0.291$), no effect of proportion (F (1, 20) = 0.378, p = .546, $\eta_p^2 = 0.019$) and no significant interaction between proportion and session number (F (2.56, 51.3) = 0.844, p = .461, $\eta_p^2 = 0.040$). Pairwise comparisons of the *k* values between the first and the succeeding sessions revealed an increase from the third session ($p \leq .002$, alpha = 0.0125). Thus, task practice with both proportions resulted in an equivalent increase in the criterion.

4.3.3. Accuracy

Because the participants had no information on the stimuli proportions, the performance should rely initially on the participant's prior belief about the proportions and, as practice progresses, the performance should be a consequence of the sensory evidence accumulated throughout practice. Moreover, the manipulation of the proportions should induce a response bias in the opposite directions for the 80-same and 80-differerent groups. As expected, each group had a differing performance for same and different pairs as shown in Fig. 7A and SF10. For a majority of same pairs (80-same), there was a similar increase in accuracy of same and different pairs and for a majority of different pairs (80-diff), there was a greater increase in accuracy of different pairs.

Specifically, in the 80-same group, the accuracy for same pairs increased from M = 0.639, SD = 0.097 in the first to M = 0.778, SD = 0.152 in the fifth session and from M = 0.670, SD = 0.186 in the first session to M = 0.823, SD = 0.104 in the fifth session for different pairs. The ANOVA showed a main effect of session number (F (4, 40) = 24.7, $p < .001$, $\eta_p^2 = 0.712$), no effect of pair type (F (1, 10) = 0.636, p = .444, $\eta_p^2 = 0.060$) and no interaction between session number and pair type (F (4, 40), p = .982, $\eta_p^2 = 0.010$). Pairwise comparisons between the first and the succeeding sessions showed an improvement in accuracy from the second session ($p \leq .002$, alpha = 0.0125). These results demonstrate that unsupervised learning with a majority of same pairs was based on an equivalent increase in performance for same and different pairs.

In contrast, in the 80-diff group the accuracy for same pairs increased from M = 0.635, SD = 0.139 in the first session to M = 0.716, SD = 0.172 in the fifth session and the accuracy for different pairs increase from M = 0.680, SD = 0.165 in the first session to M = 0.899, SD = 0.078 in the fifth session (Fig. 7B and SF11). Interestingly, the ANOVA showed a main effect of pair type (F (2.02, 20.2) = 6.42, $p < .001$, $\eta_p^2 = 0.391$) in addition to the effect on session number (F (2.02, 20.2) = 11.9, $p < .030$, $\eta_p^2 = 0.544$) but no interaction between session number and pair type (F (1.65, 16.5) = 2.77, p = .100, $\eta_p^2 = 0.217$). Pairwise comparisons of accuracy between the first and the succeeding sessions showed a difference from the third session ($p \leq .006$, alpha = 0.0125). Pairwise comparisons of accuracy for same and different pairs from the second to the fifth sessions showed a marginal but significant difference in the fourth (p = .008) and fifth (p = .0124) sessions (alpha = 0.0125). These results indicate that with a majority of different pairs, unsupervised learning was based on a greater increase in performance for different pairs. Overall, these results demonstrate that unsupervised learning for different proportions leaded to asymmetrical performance, indicating that this manipulation

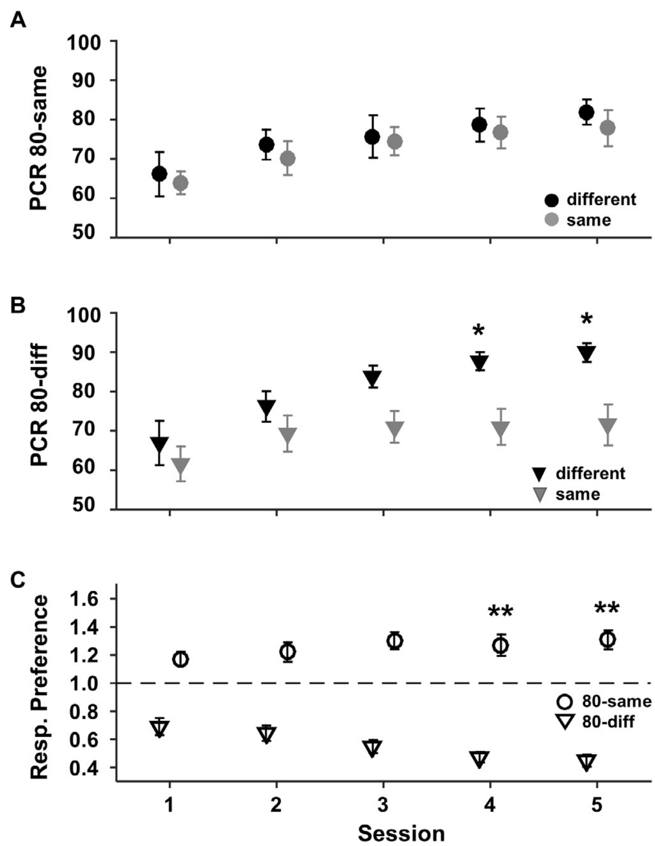

Fig. 7. Accuracy and response preference for unequal proportions of same-different stimuli. A. Percentage of correct responses (PCR) for same (gray circle) and different (black circle) pairs during discrimination practice with a majority of same pairs (80-same). B. PCR for same (gray triangle) and different (black triangle) pairs during discrimination practice with a majority of different pairs (80-diff). C. Mean response preference for the 80-same (circle) and the 80-diff (triangle) groups (*, $p < 0.05$; **, $p < 0.01$). Error bars are SE of the mean.

induced a proportion-related response bias.

4.3.4. Response bias

In the hypothetical condition of perfect performance, for a majority of same pairs the response preference should be 1.6, calculated as 80 divided by 100, multiplied by 2, and for a majority of different pairs the response preference should be 0.4, calculated as 20 divided by 100, multiplied by 2. If the manipulation of the proportions do not reduce or eliminate de bias observed in experiment 1 as would be expected if these biases were founded on independent processes, the response preference should include the bias of experiment 1 in addition to the response bias for the unequal proportions of stimuli. Therefore, the response preference should be the mirror image pattern expected for unequal and inverse proportions shifted towards *different* responses.

Because participants did not receive information about the stimuli proportions, both groups likely had an initial response preference based on individual prior beliefs, and because these are expected to be variable, we anticipated a group average close to the response preference of 1.0, corresponding to equal *same* and *different* responses. As the practice increased, the response preference should move away from 1.0, towards 2.0 for a majority of same pairs and in the opposite direction (0.0) for a majority of different pairs. Our results are consistent with this configuration as shown in Fig. 7C and SF12 including a proportion-induced response bias and a perceptual bias. Specifically, in the 80-same group, the response preference increased from M = 1.17, SD = 0.164 in the first to M = 1.31, SD = 0.223 in the fifth session, indicative of a response preference towards *same*. In the 80-diff group, the response preference decreased from M = 0.690, SD = 0.202 in the first to M = 0.448, SD = 0.144 in the fifth session, indicating a shift in response preference towards *different*. To compare the response preference for both proportions, the values for the 80-same group were inverted (2 – response preference, see methods). Interestingly, the ANOVA showed a main effect of session number ($F(2.59, 51.9) = 11.03$, $p < .001$, $\eta_p^2 = 0.356$) and proportion ($F(1, 20) = 6.96$, $p = .016$, $\eta_p^2 = 0.258$), and no interaction between session number and stimuli proportions ($F(2.59, 51.9) = 1.63$, $p = .198$, $\eta_p^2 = 0.076$). Pairwise comparisons of response preference between the first and succeeding sessions showed an increase beginning with the third session ($p < .001$, alpha = 0.0125). Pairwise comparison of response preference between proportions from the second to the fifth sessions revealed a greater response preference for 80-diff proportion in the fourth and fifth sessions ($p \le .007$, alpha = 0.0125). Moreover, the response preference for both proportions was different from 1.0 ($p \le .009$, alpha = 0.0125) in all sessions. These results show that task practice resulted in a distinct response preference for 80-same and 80-diff proportions, in agreement with a proportion-dependent response bias in addition to the bias towards *different* response observed in experiment 1. In summary, these results suggest that these biases are based on independent processes and suggests that the bias observed in experiment 1 is a perceptual bias.

4.4. Discussion of experiment 2

The main objective of the second experiment was to test if the bias of experiment 1 was a response bias. In perceptual decisions, two types of biases have been distinguished: a response bias and a stimulus processing or perceptual bias (White & Poldrack, 2014). A response bias occurs when there is a preference for a specific response, for example if the feedback is biased or if one of the options receives a greater reward. A stimulus processing bias occurs if there are differences in how the evidence extracted from the stimuli is used to select the behavioral choice. A response bias can be dissociated from a perceptual bias through manipulations of stimuli proportions and rewards (Leite & Ratcliff, 2011). Earlier work showed that manipulations of the stimuli proportions modify the response bias, but had no effect on the perceptual bias (Ashby, 1983). Using this evidence, in the second experiment we manipulated the proportion of stimuli without the participant's knowledge, to induce a response bias. Thus, we evaluated if this manipulation reduced or eliminated the bias observed in experiment 1, as would be expected if both biases were rooted on the same process. First, we confirmed the unsupervised learning for unequal proportions as an increase in sensitivity and criterion with practice (Fig. 6). Our results show no significant differences in the sensitivity and criterion between proportions. Interestingly, there was a tendency for a greater sensitivity and lower criterion in the 80-diff group, suggesting that with additional sessions, greater difference in proportions or more participants may reach significance. Further studies are necessary to evaluate this possibility.

Nonetheless, a proportion-induced bias was evident in the accuracy for same and different pairs individually and in the response preference. There was a response preference of greater than 1.0 in the 80-same group and a response preference lower than 1.0 in the 80-diff group and both increased as the practice increased. In addition to the expected proportion-induced bias in the response preference, there was an additional shift in the response preference in the same direction for the 80-same and 80-diff groups, corresponding to the bias observed in experiment 1. Although, the differences in the performance with same and different pairs for kanji and checkerboards exhibit a low power due to the small number of participants in each group, the consistency of the results of experiment 1 and 2 represent a replication and thus, a validation of the greater accuracy with different pairs and the response preference. In summary, the manipulation of proportions induced a response-bias without reducing or eliminating the bias observed in experiment 1. We conclude that the bias from experiment 1 is very likely of perceptual nature and in consequence, it takes place in the stimulus processing stages (Leite & Ratcliff, 2011).

5. General discussion

Our study investigated whether discrimination learning is accomplished through unsupervised practice of same-different judgments and if this learning generalizes to the trained category. Our main findings are: 1) unsupervised training leads to visual discrimination learning, 2) the discrimination learning is characterized by increases in the stimuli discriminability and shifts in the criterion that reflect a perceptual bias and 3) unsupervised discrimination practice leads to the acquisition of domain specific abilities for the trained category in agreement with the acquisition of perceptual expertise.

5.1. Unsupervised training

Here we show that unsupervised practice of a visual discrimination task with multi-exemplar complex stimuli is sufficient for visual discrimination learning. By unsupervised learning we mean task conditions that do not include information about the correct category of each exemplar during training, such as stimulus labeling and feedback on performance (Tian & Grill-Spector, 2015). Several studies indicated that visual learning of complex unfamiliar stimuli requires stimulus naming or categorization at the subordinate level (Scott et al., 2006; Scott et al., 2008; Tanaka, Curran, & Sheinberg, 2005; Wong et al., 2009) to reach expert-like levels of performance. More recently, this idea has been challenged as discrimination learning was obtained during training with individuation, in the absence of stimulus naming or categorization at the subordinate level (Bukach et al., 2012) and during same-different training with artificial 3 D images in unsupervised conditions (Tian & Grill-Spector, 2015).

In addition to the stimulus label and categorization at the subordinate level, the provision of feedback on performance constitutes another source of information about the correct responses and thus, contributes to supervised learning. The feedback on performance increases the performance levels (Herzog & Fahle, 1997) and modify the sensitivity or the criterion depending on the feedback regime provided (Aberg & Herzog, 2012). The majority of studies on visual learning of complex unfamiliar stimuli have provided feedback on performance (Scott et al., 2006; Scott et al. 2008; Tanaka, Curran, & Sheinberg, 2005; Wong et al., 2009), with a few exceptions (Bukach et al., 2012; Scott et al., 2008; and Tian & Grill-Spector, 2015). In supervised conditions, the feedback provided may reduce or eliminate any bias that occurs during unsupervised learning. Therefore, the feedback may provide additional information to the accumulated sensory evidence that may increase performance. However, we cannot rule out that supervised training will lead to greater performance levels by speeding up learning or by modifying the sensitivity or the criterion (Aberg & Herzog, 2012), which results in greater proportion of correct responses if there is a reduction in a bias. According to the SDT model, the maximum proportion of correct performance for a given sensitivity index is obtained by an observer that has no bias. Further studies should compare the progression and the maximum levels of performance in unsupervised and supervised conditions. In conclusion, we show that unsupervised discrimination training is sufficient for discrimination learning.

5.2. Bias

In addition to the expected increase in discriminability with practice, there was a shift in the decision criterion and a significant bias in the response with both stimuli types. Even though the number of participants was low, the results were similar with kanji and checkerboards in experiments 1 and in the different response preference for the 80-same and 80-diff groups in experiment 2. Thus, we considered this a replication of the results and a validation of the observed bias towards *different* after several sessions of practice. There is limited evidence on biased response selection or differences in performance for same and different pairs individually, because the majority of studies have focused on practice-dependent modifications on sensitivity and total accuracy. However, a few studies reported differences in the performance for same and different pairs. In supervised tasks with familiar stimuli, greater errors on same pairs were found in pitch discrimination (Coltheart & Curthoys, 1968) and simultaneous letter discrimination (Proctor & Rao, 1983). In supervised tasks with unfamiliar stimuli, a small but greater accuracy for different pairs was reported (Chen et al., 2013). On the contrary, supervised auditory discrimination practice reduced a bias observed in novices (Jones et al., 2015). A single study in unsupervised discrimination of artificial 3D images resulted in greater reduction of errors for different pairs in certain conditions (Tian & Grill-Spector, 2015). Finally, there was no learning after unsupervised attentive exposure to car models (Scott et al., 2008). We considered two main differences in the tasks and procedures between these studies that might explain the incongruous results, such as the feedback on performance and the familiarity with the stimuli. Specifically, the feedback on performance may induce or modify a bias (Herzog & Fahle, 1999) and the familiarity with the stimuli might modify its processing from featural to holistic or configural processing, typical of expertise acquisition (Wong et al., 2009).

Typically, a bias in the response selection originates from a response bias, based on a conscious decision to select one of the response options; or from a perceptual bias, based on differences in stimulus processing. In turn, a response bias may originate from a feedback on performance (Chen, Jimura, White, Maddox, & Poldrack, 2015; Herzog & Fahle, 1997; Herzog & Fahle, 1999), instructions on stimuli proportions (Leite & Ratcliff, 2011) or differential rewards (Herzog & Fahle, 1999). In our experiment, participants did not receive feedback or differential rewards, and were informed about an equal proportion of stimuli. Thus, either feedback- or a proportion-related decisional process did not generate the observed bias. However, the presence of a bias in our experiments may arise from the absence of feedback on performance, which when present might reduce or eliminate the bias observed in unsupervised conditions.

Alternatively, the bias may arise from an internal signal related to stimulus processing such as information extraction, maintenance in memory and posterior evaluation of the sensory evidence, all reflecting a bias in stimulus processing (Jones et al., 2015). It is known that different types of practice can improve the ability to discriminate between stimuli shapes (Gauthier & Tarr, 1997; Op de Beeck et al., 2006) and this improvement has been attributed to the acquisition of holistic or configural processing of the stimulus (Richler, Wong, & Gauthier, 2011). The holistic or configural processing may contribute to changes in stimulus information extraction, which may have distinctive effects on same and different pairs if there are differences in the type of information required for the correct classification of different and same pairs as proposed by Aly and Yonelinas (2012). For example, if the detection of differences requires the selection of the relevant parts of the stimulus and the detection of matching pairs requires the evaluation of the whole stimulus. In addition to the differences in stimulus information extraction, the bias may originate of differences in the working memory processes involved either in the discrimination of sequential stimuli or in the mental rotation of the first stimulus required to compare it with the second stimulus. For example, if the information of the first stimulus is not fully coded in working memory because of reduced resolution for unfamiliar stimuli (Scolari, Vogel, & Awh, 2008; Lorenc, Pratte, Angeloni, & Tong, 2014; Brady, Störmer, & Alvarez, 2016), or if the information in working memory is subjected to variability during its maintenance (Fougnie, Suchow, & Alvarez, 2012; Lepsien, Thornton, & Nobre, 2011) reducing the matching of same pairs compared to detection of differences. Interestingly, the matching of a stimulus with working memory contents for same pairs requires less information (Gayet, van Maanen, Heilbron, Paffen, & Van der Stigchel, 2016). Thus, the holistic or configural processing of stimulus typical of expertise performance would promote faster information extraction for short stimulus durations, better coding in memory (Scolari et al., 2008), and better mental rotation as parts and relations of the stimulus are kept together with holistic processing (Xu & Franconeri, 2015). In conclusion, the bias with increasing sitmuli familiarity reveals practice-dependent modifications of the stimulus processing.

5.3. Specificity of the discrimination learning

Our results show an almost complete generalization of the learning to novel exemplars of the practiced category, indicating that practice led to expert-like learning with both kanji and checkerboards stimuli as previously shown in supervised training conditions (Gauthier & Tarr, 1997; Gauthier et al., 1998; Tanaka, Curran, & Sheinberg, 2005; Wong et al., 2009). Our results suggest that unsupervised discrimination learning is consistent with modifications in the stimulus processing that increase the sensory evidence (Sigman & Gilbert, 2000) and/or the precision of the working memory in a domain specific manner (Curby & Gauthier, 2010).

In our study, we did not evaluate additional properties of expert-like object perception such as the sensitivity to configural changes and the holistic processing of the stimulus (Richler et al., 2011; Wong et al., 2009). Further studies should evaluate the changes in the stimulus processing. We conclude that unsupervised discrimination of complex stimuli lead to a domain specific ability to process a stimuli category and to achieve high discrimination sensitivity distinctive of experts (Bukach et al., 2010).

6. Conclusions

This study provides evidence for expert-like unsupervised learning of complex stimuli during practice of perceptual comparisons based on the adjustment of the criterion in addition to the increase in the stimuli discriminability. In naïve observers, accuracy for same and different pairs was low and equi-probable. As observers became familiar with the stimuli, accuracy for different pairs became greater, and a marker of this divergence was the bias in the response preference towards *different* response. The manipulation of proportions to induce a response bias indicated an independent process underlying the bias with equi-probable stimuli. Overall, these results suggest that unsupervised learning is rooted in changes in the stimulus processing that include a better perceptual sensitivity, which increase the sensory evidence and/or the precision of the working memory for the stimuli, and a perceptual bias. Despite the limited number of practice sessions in the present work, it was sufficient for the acquisition of a domain-specific ability for processing the stimuli category and for achieving high discrimination sensitivity. Moreover, participants learned to discriminate complex stimuli without practicing explicit object naming or categorization at the subordinate level, previously held as necessary to achieve expert-like performance. We conjecture that in conditions of greater levels of expertise than the ones obtained in this work, observers may reach an equivalent performance with same and different pairs, as has been observed for simple stimuli. Further studies are needed to evaluate how the different levels of familiarity modulate the perceptual bias and the contribution of the perceptual processing and the precision of the working memory to the visual discrimination learning. The understanding of the properties of unsupervised learning is highly relevant as learning from natural statistics is typical of humans (Li & DiCarlo, 2010; Saffran & Kirkham, 2017) and some animals (Santolin & Saffran, 2018).

Acknowledgements

The authors are grateful to David Gomez and Michelle Dragan for the comments on an earlier version of this manuscript. This work was supported by Becas CONICYT and Becas Chile (RMS), Fondecyt 1150289, Fundación Puelma, Basal Funds for Centers of Excellence FB0003 (MT, MLA) and Iniciativa Científica Milenio ICM P04-068-F (PM, MLA).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.visres.2018.05.002.

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