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5 **Seeing the World from Above:**
6 **Training with Aerial Scenes Reveals the Effects of**
7 **Experience on Scene Recognition**
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Abstract

Throughout evolution, the human visual system has adapted to efficiently encode several environmental constants to deal with the huge complexity involved in representing large-scale spatial environments. Being terrestrial animals, these constants reflect a specific ground-based viewpoint. For example, people show a strong affinity for detecting a perceptual upright layout relative to the horizon. But, what happens when humans leave this terrestrial perspective, for example when taking a flight, or looking down from the Empire State building? Are the mechanisms originally evolved for terrestrial scene recognition also recruited for the recognition of novel large-scale environments people rarely encounter on a daily basis? We propose that studying how people learn to recognize aerial scene images can reveal how the scene recognition system develops through experience and shed light on the putative mechanisms underlying its malleability. We conducted an intensive six-session behavioral training study in which naive participants learned to categorize manmade and natural scenes at a specific-subordinate level ('suspension bridge'). Scene images depicted real-world places from a terrestrial and an aerial viewpoint, allowing us to establish how people learn to categorize two visually-different images as the same environment. We found that performance constantly improved over the first five training sessions, with greater learning for the aerial compared to the terrestrial scenes. This viewpoint performance gap manifested more for manmade than natural scenes. In addition to memory improvements, we also found learning transfer, the hallmark of perceptual learning. Performance in the sixth session (in which participants categorized scenes they had not been trained with) was significantly better compared to the first session, and equivalent to average performance across training-sessions. Our findings provide novel evidence

60 for the potential mechanisms underlying plasticity in the scene recognition system, showing both
61 memory and perception contribute to experience-based enhancements in scene recognition.

Seeing the World from Above: Training with Aerial Scenes Reveals the Effects of Experience on Scene Recognition

Humans are extremely adept at recognizing complex visual scenes, an ability developed over years of navigating and visually exploring their surrounding environments, both manmade and natural spaces (Chai et al., 2010; Ofen et al., 2012; Meissner et al., 2019). People categorize scenes with minimal effort across varying behavioral contexts and along multiple dimensions (Malcom, Groen & Baker, 2016), detect object and anomalies within scenes (often difficult for visual recognition systems to model, Bergman et al., 2019), and store and retrieve a substantial number of scenes in visual long-term memory capacity (Brady, Konkle, Alvarez & Oliva, 2008). These remarkable abilities are supported by a network of dedicated cortical regions in posterior-parietal, occipital, and medio-temporal cortex (Epstein & Baker, 2019), which develop increasing specializations over the course of childhood (Meissner et al., 2019; Kamps et al., 2020). Despite the growing knowledge of these areas and their developmental trajectories, much less is known about the malleability and plasticity of the adult scene recognition system.

Specifically, can people develop skills in scene recognition - above and beyond their existing everyday scene recognition abilities, or is it the case that scene recognition fully matures by adulthood and reaches a performance plateau? Additionally, if the adult scene recognition system is plastic into adulthood, how exactly does experience impact visual scene processing?

While the effect of experience on visual perception has been studied extensively, the majority of research is usually focused on how people recognize simple visual properties and meaningless shapes (i.e. perceptual learning: Fahle et al., 2002) or everyday objects (Palmeri & Gauthier, 2004). There is very little research on the effects of experience on scene recognition which is particularly surprising compared to the large body of research on expertise in object

recognition (Harel et al., 2013; Harel, 2016). This is surprising for two reasons: First, from a theoretical perspective, scenes actually provide a better approximation of real-world vision, as scenes can be considered snapshots of our surrounding environments, which is the first step in comprehending events in our environment (Loschky et al., 2020). In that sense, it may be argued that scene recognition subsumes and extends object recognition (Henderson & Hollingworth, 1999). Second, a wide variety of professions and contexts do involve extensive training in recognizing or interacting with scene images, yielding fast and efficient scene recognition (e.g. overhead imagery analysis, remote sensing, land surveys, weather prediction). This demonstrates that people can and do develop expertise in scene recognition. That is, scene recognition is plastic. Critically, however, the nature of the underlying mechanisms which enable the development of such skills in recognizing the visual environment are still undetermined.

One clear example of a domain that requires expertise in scene recognition is analysis of aerial scene imagery (Lloyd, Hodgson, & Stokes, 2002; Šikl et al., 2019). Recognizing aerial scenes presents unique challenges to the human visual system. Since humans are terrestrial animals, the visual system has adapted to efficiently encode a number of environmental constants, or diagnostic features, that reflect a ground-based viewpoint (Greene & Oliva, 2009) rather than an aerial one. An example of this is the detection of horizontal and vertical edges nested within the perceptual upright layout relative to the horizon (the gravitational frame; Loschky, Ringer, Ellis, & Hansen, 2015; Ringer & Loschky, 2018). These diagnostic features are absent or completely transformed in aerial scenes. These include limited configural information, obscured object referents and terrain information, as well as other diagnostic features which people are simply unfamiliar with. Configural information and familiar statistical regularities are not present in aerial scenes as they contain a high degree of spatial homogeneity, which make

108 them more difficult to encode and discriminate (Loshky et al., 2015). Crucially, to overcome
109 these challenges usually requires intensive training and long-term experience. Therefore,
110 studying aerial scene recognition and specifically, how the acquisition expertise within this
111 domain is formed can provide us with insights into how existing scene recognition mechanisms
112 might accommodate novel, never-seen-before types of visual environments. The key question is
113 to what extent the same perceptual processes and neural mechanisms – originally evolved for
114 terrestrial scene recognition – are recruited for the recognition of novel, complex scenes.

115 One possibility is that existing scene recognition mechanisms are recruited to support
116 aerial scene recognition. Evidence for this idea comes from the very few neuroimaging studies
117 that studied aerial scene recognition (Shelton & Gabrieli, 2002; Shelton & Pippit, 2006; Barra,
118 Laou, Poline, Lebihan, & Berthoz, 2012). These studies show that the same scene-selective areas
119 that support everyday (terrestrial) scene recognition also support the processing of aerial scenes
120 including PPA (parahippocampal place area; Epstein & Kanwisher, 1998), OPA (occipital place
121 area; Dilks, Julian, Paunov, & Kanwisher, 2013), and RSC/MPA (retrosplenial complex/medial
122 place area; Silson, Steel, & Baker, 2013). However, one limitation of these studies is they
123 involve subjects with only minimal experience with the aerial scenes, thus leaving open the
124 question of how *long-term* experience mediates the recognition of aerial scenes. One option is
125 that developing expertise in aerial scene recognition recruits existing perceptual processes,
126 evidenced by the involvement of core scene recognition areas. However, the scene recognition
127 network constantly interacts with additional large-scale cortical networks to support spatial
128 memory and navigation (Epstein & Baker, 2019), suggesting the possibility that additional
129 higher-level processes are involved in expert (aerial) scene recognition. Examples of such
130 processes include top-down selective attention (Ahissar & Hochstein, 2004), semantic

knowledge (Harel, 2016), and spatial navigation (Maguire et al., 2003). Expert image analysts' (i.e. trained geographers) visual recognition memory performance for a variety of aerial scene images was found to be substantially more accurate compared to novice geographers. The experts enhanced visual recognition memory is suggested to be facilitated by the concurrent use of semantic and visual information enabling the construction of distinct representations in memory (Šikl et al., 2019). Visual expertise in aerial scene recognition may thus emerge from the interaction between perceptual and semantic categorization processes, with increasing semantic knowledge guiding the extraction of task-relevant diagnostic features (Harel et al., 2010; Harel et al., 2013, 2014, Harel, 2016).

In the present study we aimed to determine the cognitive mechanisms underlying the acquisition of expertise in aerial scene recognition as a way of establishing how experience impacts the scene recognition system. In line with the interactive view of expertise (Harel et al., 2013), we designed a training study that emphasized the formation of semantic memory associations in conjunction with learning a challenging perceptual task. Naïve subjects undertook a long-term training regimen that emphasized both increased semantic knowledge of places, and the formation of generalized perceptual representations of those places. We utilized a category verification paradigm which constrains the specificity level of categorization (Harel & Bentin, 2009) to examine the extent to which semantic labelling impacts perceptual categorization of aerial and terrestrial viewpoints of scenes of the same place. The formation of viewpoint-invariant representations is considered an index of experience both in object recognition (Gauthier et al., 2002) and spatial cognition (Friedman & Waller, 2008; Livingstone-Lee et al., 2014). For instance, the formation of viewer-independent, allocentric representations from egocentric viewpoints in navigation, also known as perspective taking ability, has been found to

be predictive of the ability to learn spatial layout based on navigational experience (for a review see Wolbers & Haggerty, 2010). Scenes are processed in a view-dependent manner, based on the similarity between the perceptual input and previously encoded representations (Christou & Bühlhoff, 1999). Experience with a particular scene across various positions will yield viewpoint-independent representations that can produce fast and efficient processing akin to the formation of viewpoint-invariant object representations with increasing experience (Kravitz, Vinson, & Baker, 2008). Thus, in the present work we aimed to establish how people develop mental correspondences between two different viewpoints of the same type of scenes over the course of extensive training as means of assessing the formation of visual expertise in scene categorization (see also Loschky et al., 2015). The rationale for using two viewpoints of the same place was to determine the extent to which scene expertise involves an increase in the observer's ability to extract invariant information from one viewpoint and apply it to another.

We constructed a rich multi-dimensional stimulus set consisting of high-resolution color images of diverse scene categories, spanning five independent dimensions: Viewpoint (aerial and terrestrial), Naturalness (manmade and natural), and three levels of categorization in increasing specificity: Basic-level category (the particular manmade or natural category), Subordinate-category (specific categories within each basic category), and Exemplar (a particular place, e.g. "Nationals Park"). We trained a group of participants across several weeks to recognize the aerial and terrestrial scenes at their subordinate category labels (e.g. small airport, large airport, military airbase) within the same basic category (airport), requiring participants to make fine discriminations among visually similar subordinate class members. We asked whether training people to visually categorize aerial and terrestrial scenes at the subordinate level would result in enhanced categorization performance and, critically, whether these newly acquired skills would

transfer to novel scenes, indicating changes to perceptual processing. To assess the efficiency of the training regimen, we employed three behavioral metrics: (1) within-set learning (learning across training sessions of same scene stimuli), (2) generalization to new exemplars (transfer of learning), and (3) generalization across viewpoints. We made the following hypotheses regarding the respective metrics:

Within-Set Learning

We hypothesized that, overall, participants would start out as novices, with relatively poorer performance in earlier sessions, and that by the final training session they would reach high levels of performance in categorizing scenes across multiple image dimensions. Further, since aerial scenes are processed less efficiently than terrestrial scenes (Ringer et al., 2018; Šikl et al., 2019), we hypothesized that categorization of aerial scenes at baseline would be poorer than that of terrestrial scenes. However, at the same time because of the participants' unfamiliarity with viewing scenes from an aerial perspective (Loschky et al., 2015) we predicted greater learning for aerial scenes compared to terrestrial scene learning.

Transfer of Learning

In addition to memory-based learning established across five training sessions, we hypothesized that participants would utilize the knowledge formed during training to successfully categorize novel (unseen) scenes presented in their sixth and final session. Skill transfer to novel scenes requires generalizing newly formed semantic associations and perceptual strategies to new situations (Goldstone, 1998; Schyns, 1998). Accordingly, it is likely that subjects will form unique sets of diagnostic features for the different kinds of scene dimensions. For example, to categorize whether a terrestrial scene depicts a small airport, the visual system may attend to available objects (e.g. small planes, grass runways) as diagnostic cues to differentiate it from

other kinds of airports. Critically, we hypothesized that such sets of diagnostic features are learned throughout training, not just simply memorized, allowing people to extract the identity of new exemplars of the same scene categories they were exposed to.

Generalization Across Viewpoints

One open question is the extent to which diagnostic scene features are specific or generalizable, that is, also diagnostic for categorizing the same scene across different viewpoints. Each exemplar represented a single place, both in a terrestrial and an aerial viewpoint, allowing us to determine the extent to which scene expertise involves an increase in the observer's ability to extract invariant information from one viewpoint and apply it to another. All terrestrial and aerial scenes from the same subordinate category were presented under a common semantic label regardless of viewpoint, requiring participants to recognize distinctive images as belonging to the same category. The question we posed is whether these different images are actually treated as the *same entity*. One possibility would be that they are *visually* recognized independently, and then the common label gets assigned post-perceptually. In that case, one would expect equivalent improvements over the course of training for both viewpoints. Alternatively, over the course of training, some previously unattended diagnostic features become relevant to the learner, features which index viewpoint-invariant commonalities across the two viewpoints of the same place. As an analogy of the latter, one could be trained in categorizing two face images of the same person across two very different age ranges (i.e. as a young child and as an adult), during which they will develop a set of new facial identity features that are age-invariant (George & Hole, 1998). In the current context, this would translate to a "bridging" of the performance gap between viewpoints over the course of training, and crucially, this bridging should also be observed with novel exemplars, that is, generalize to novel images participants have not previously categorized.

Methods

Participants

Participants were recruited from the Wright State University community. All subjects had normal or corrected-to-normal visual acuity and no history of psychiatric or neurological disorders as self-reported. Participant consent was obtained during a scheduled 10-minute session for the purpose of informing the participant about the experiment background and procedure as well as answering any questions the participant might have concerning the experiment or participation. Participants provided their written informed consent, as well as signed a HIPAA authorization form. The consent form, HIPAA authorization form, and the experimental protocol were approved by the Wright State University Institutional Review Board (IRB). During the consenting session, six experimental sessions were scheduled for each participant. We recruited 55 subjects to participate in the experiment for monetary compensation. Insufficient behavioral performance ($< 80\%$ accuracy), corrupted data, and/or failing to complete the full six training sessions resulted in removal from further analyses (a total of 8 participants were removed). Consequently, 51 participants (control $n = 21$ (12 females, mean age = 23.57, $SD = 3.23$) and experimental $n = 30$ (17 females, mean age = 24.75, $SD = 3.67$) were used for the analyses reported here.

Apparatus

Participants performed each experimental session on a desktop computer (Dell Optiplex), running Windows 7 as the operating system. The experiment was created in, and displayed with Neurobehavioral Systems Presentation (Neurobehavioral Systems, Inc, Berkley, CA, www.neurobs.com). A Python script was used for generating subject stimulus lists. The task was displayed on a computer monitor and participant responses were made via mouse-clicks.

Participation took place in individual experiment rooms, containing a single computer, mouse, and keyboard with which to perform the task. Stimuli were displayed on a 24" LCD monitor at a viewing distance of approximately 57 cm. Each image was 600 x 400 pixels in size (subtending 15.88° x 10.52° visual angle). All stimuli were displayed at the center of the screen on top of a grey background (RGB: 152, 152, 152; CIE xyY: 0.345669, 0.358496, 151703.566212).

Stimuli

In total, 480 high-resolution color images of diverse scene categories that spanned five dimensions were used within the present study. The images were obtained from Google Maps, Google Images, Bing Maps, and Bing Images under the Creative Commons License in order to develop an expansive and diverse set of scene images. Each physical location within the image set was represented by both a terrestrial image, and an aerial image (i.e. two images exist of each physical location within the image set, one viewed from the ground, and one viewed from the air). Aerial images were captured specifically using Bing Maps and elevation levels were controlled to be between 300-500ft. We determined 300-500ft was an appropriate elevation range to capture sufficient diagnostic information for all scene categories necessary to make a subordinate category judgment.

The images spanned five independent stimulus dimensions and were selected from online sources in order to represent these dimensions. The semantic content of the scene images dictated the relative representation of each of these dimensions. We examined each of the following dimensions:

Viewpoint

The scene images were from two viewpoints. The terrestrial viewpoint refers to scene images viewed from the ground and are typical of how someone would view a scene in everyday life. They are often characterized by a horizon and converging perspective lines. The aerial viewpoint refers to a "birds-eye view" of a scene. Because of the overhead viewpoint, perspective lines are not present within the aerial images. Additionally, due to the elevation from which the images were taken, the same amount of detail was not necessarily present as there was in the terrestrial images.

Semantic Content (Naturalness)

The total collection of images was split by the semantic content of the images: manmade and natural scenes. Half of the images are composed of manmade scenes, defined as scenes with a majority of the content being manmade in nature (e.g. buildings, roads, furniture, etc.). The other half of the images are composed of natural scenes, defined as scene images containing mostly natural content (e.g. water, trees, rocks, etc.).

Basic Category

Each image fits into one of 8 categories, half of which are natural categories, the other half being manmade. The natural categories consist of scenes in which the contents are entirely naturally occurring (e.g. plant life, rock formations, etc.), and are all devoid of any obvious human influence. The natural categories are bodies of water, deserts, land types, and mountains. Manmade categories all contain prominent human influences within the scenes. The manmade categories are settlements, airports, stadiums, and bridges.

Subcategory

In addition to the images being divided into 8 basic categories, each individual category has 3 subcategories (e.g. bridges: truss, suspension, arch). These subcategories are what

participants make the category membership judgment based upon, allowing the task to be more engaging and the distinctions between subcategories to be more subtle. Participants were tested on the subcategory of the images by making a member/non-member judgment (i.e. category verification). This means that chance performance in this design would be 33%.

Exemplar

Within each subcategory there are 10 individual exemplar images (for both terrestrial and for aerial). Each exemplar within either of the two viewpoints is an image of a distinct place on Earth. However, each physical location is represented by two exemplars, one of a terrestrial view, and another of an aerial view. This is true across the entire stimulus set, allowing us to examine effects that are elicited by viewpoint invariant characteristics of the scenes.

Each subset of aerial and terrestrial images consisted of 240 images; 120 manmade and 120 natural scenes, 4 categories for each manmade/natural dimension, manmade dimension: airports, bridges, stadiums, and settlements; natural dimension: mountains, deserts, landforms, and bodies of water. Each of these categories contained three subcategories, and ten exemplars within each sub-category. For example, the category “deserts” contained three types of deserts: Sandy, Shrub and Rocky, and each of these types of desert contained ten individual images of specific desert landscapes (for examples of the scenes used, and the category labeling hierarchies, see Figure 1).

Figure 1

Figure 1. Examples of scene stimuli used in the study and their category labels. Each image depicted the same place from a terrestrial and aerial viewpoint (depicted here are one of ten exemplars for each category). The images span both natural and manmade categories, four categories within each (Natural: Mountains, Land Types, Bodies of Water, Deserts; Manmade: Airports, Settlements, Bridges, Stadiums). Each subcategory contained three subordinate categories as labeled here (labels were not presented during the neuroimaging sessions).

Procedure

The training program consisted of 6 training sessions over the course of three weeks (two per week), each session lasted approximately 2 hours, for a total of 12 hours of training over the course of the entire experiment. The first 5 sessions assessed learning with the same stimuli (within set learning), and the sixth session was used to assess generalization (transfer of learning) using a set of new scene stimuli. Scene images used for the learning stages were selected randomly for each participant, so that each participant saw a unique set of scene images. Scene stimuli for the first five sessions were one half of the allowable exemplar set, in this case, 240 of the possible 480 images. The same procedure was applied in the transfer learning session, the only difference being that the remaining 240 images from the exemplar stimulus set were used. The method by which we created these stimulus sets for each participant also maintained the organization and representation of the stimulus dimensions within each of the separate lists. The

splitting of the full image set was accomplished by iterating through each combination of stimulus dimension values (e.g. aerial viewpoint, naturalness semantic content, bodies of water category, etc.), and pseudo-randomly (Mersenne Twister) sampling five exemplars from each collection of ten possible exemplars fitting those stimulus dimension values. The sampled exemplars were placed into the training set, whereas the remaining 5 images within each collection of exemplars was placed within the testing set. This allowed us to split the full image set into separate training and testing sets that were different for each participant yet maintained the same representative dimensions as the full set, while additionally varying the images used for testing and training.

The unique advantage of the category verification paradigm is that it controls for participants' categorization of the visual image. It does so by preceding the image with a label at a given level of specificity, thereby constraining any potential idiosyncratic categorization schemes. A typical trial in our experiment started with the label of a specific subcategory (e.g. "sandy desert"), followed by the image of the scene to be categorized, which could either be consistent (e.g. a sandy desert) or inconsistent with the label (e.g. a rocky desert). Every image was presented three times during the session (consistent trial + 2 different inconsistent trials), culminating in 720 individual trials, together comprising a single training session. Each session was broken down to 8 blocks (4 aerial blocks and 4 terrestrial blocks, alternating each block), with 90 trials in each block.

The progression of a trial proceeded by the presentation of a white (RGB: 255, 255, 255) fixation cross in the center of the screen for a duration of 500 ms. This first fixation cross signaled to the participant that the trial was about to begin. A sub-category label (e.g. "arch bridge") was displayed centrally on the screen in white text for a duration of 2000 ms. The label

presented could be either the correct subcategory (e.g. arch bridge), or one of the two remaining subcategories (e.g. suspension bridge or truss bridge) within the same basic category (e.g. bridges) as the target image. The fixation cross was then displayed again for 500 ms for the inter-stimulus interval (ISI). Following the ISI, the target image was presented for 2000 ms in the center of the screen, after which the blank background was presented until participant response. The participant responded via mouse-click whether they thought the label described the target image. Upon responding, participants were presented with feedback. The feedback display played a sound depending upon the correctness of their response (a “ding” for correct, a “buzz” for incorrect), and also displayed information to the participant about what they responded to, as well as what the correct response was.

Control participants viewed the same scene stimuli the same number of times, across the same number of sessions (including a sixth session to assess learning transfer) as the experimental group. Control participants performed an orthogonal, passive fixation cross task overlaid on the scenes that did not require any active involvement with the scene content. Like the experimental group, 240 images of the available 480 were used for the first five training session. Control participants judged changes in a fixation cross (changes were either vertical or horizontal) for the first five training sessions. During the sixth session, control participants performed the same scene categorization task as the experimental group using a unique set of scene stimuli pooled from the other half (240 images) of the remaining exemplar scene stimuli set.

Behavioral Analyses

Mean reaction times and accuracy scores were calculated for each condition. Reaction time outliers were replaced with the participants’ session mean reaction time. Rather than using

raw reaction time and accuracy scores to perform the analyses, we calculated Inverse Efficiency Scores (IES) to accommodate speed-accuracy trade-offs (Townsend & Ashby, 1978). IES is calculated by taking mean response time divided by the proportion correct, with the resulting number being the IES. We used the IES performance measure in all subsequent ANOVAs describing the categorization efficiency. We obtained qualitatively similar results using reaction time as a measure of performance. In all statistical analyses, Greenhouse–Geisser corrections were used for non-spherical data.

To assess the efficiency of the training regimen, we employed 3 behavioral metrics: (1) within-set learning (learning across the five sessions), (2) generalization to new exemplars (transfer of learning), and (3) generalization across viewpoints.

Results

Overall, categorization performance substantially improved on all three learning measures, validating our training paradigm and demonstrating that naive participants can develop skills in quickly and accurately categorizing scenes at their subordinate level. Learning occurred within the five training sessions (evident in a monotonic decrease in IES), and notably, we also found transfer of learning, as performance in the sixth session was pronouncedly better than performance in the first four training sessions (Fig. 2). We next describe each of these findings in turn.

398 **Figure 2**

399

400 *Figure 2. Learning trajectories (IES) as a function of scene naturalness (manmade, natural) and viewpoint (aerial,*
 401 *terrestrial) for the experimental group. Efficiency of learning (in milliseconds/percent correct) increases with*
 402 *training with same scenes (Sessions 1-5) and with novel scenes (Session 6).*

403 **Within-set learning**

404 We conducted a repeated measures omnibus ANOVA on participants' performance
 405 scores, measured by inverse efficiency scores (IES) using Naturalness (manmade, natural)
 406 Viewpoint (aerial, terrestrial), and Session (1-5) as independent variables. Participants improved
 407 in categorizing the scene images over time (significant main effect of Session ($F(4,116) = 19.83$,
 408 $p < .001$, $\eta_p^2 = .41$, 90% CI $\eta_p^2 = (.276, .484)$). The most substantial learning occurred between
 409 the first session ($M = 1147$ ms, $SE = 57.88$) and second session ($M = 995.86$ ms, $SE = 47.42$), in
 410 which participants' performance improved by approximately 15% ($p < .001$). Performance
 411 progressively improved after each subsequent session, as indicated by a significant linear trend
 412 ($F(1,29) = 25.81$, $p < .001$, $\eta_p^2 = .47$, 90% CI $\eta_p^2 = (.233, .614)$), although these pairwise
 413 differences were not significantly different (Bonferroni-corrected post-hoc comparisons, $p >$
 414 0.05).

As for the effect of specific scene dimensions across the five training sessions, terrestrial scenes ($M = 908$ ms, $SE = 44.56$) were categorized more efficiently than aerial scenes ($M = 1095$ ms, $SE = 54.68$) (significant main effect of Viewpoint: $F(1,29) = 148.58$, $p < .001$, $\eta_p^2 = .84$, 90% CI $\eta_p^2 = (.725, .882)$); and natural scenes ($M = 954$ ms, $SE = 48.64$) were categorized better than manmade scenes ($M = 1049$ ms, $SE = 49.53$) (significant main effect of Naturalness: $F(1,29) = 76.11$, $p < .001$, $\eta_p^2 = .72$, 90% CI $\eta_p^2 = (.552, .801)$). Notably, the effects of these two scene dimensions were not uniform across the training sessions. Participants performance over time varied based on whether they were categorizing aerial or terrestrial scenes (significant Session by Viewpoint interaction, $F(4,116) = 8.29$, $p < .001$, $\eta_p^2 = .22$, 90% CI $\eta_p^2 = (.099, .304)$) or manmade and natural scenes (significant Session by Naturalness interaction: $F(4,116) = 21.52$, $p < .01$, $\eta_p^2 = .42$, 90% CI $\eta_p^2 = (.297, .502)$). To explore these interactions, we generated Viewpoint and Naturalness difference indices (Aerial minus Terrestrial, Manmade minus Natural, respectively) and tested how each of these indices separately varies with increasing practice. We found that the performance difference between Aerial vs. Terrestrial scenes decreased over the course of the training; at session 1 the difference was 245 ms (with an efficiency advantage for terrestrial scenes), and this gap decreased to 144 ms at session 5 (Figure 3a). This 100 ms difference was significant ($p < 0.004$, Bonferroni-corrected). Moreover, the Viewpoint effect decreased linearly with increased practice ($F(1,29) = 13.72$, $p < 0.001$, $\eta_p^2 = .32$, 90% CI $\eta_p^2 = (.099, .494)$). Planned comparisons between successive sessions showed significant differences between all successive stages (p 's < 0.05) except for the difference between third and fourth session ($p < 0.42$), indicating the “gap” between aerial and terrestrial gets progressively reduced throughout training.

To formally evaluate the increase in the amount of learning in the aerial scenes compared to the terrestrial scenes, we calculated the total learning effects for both aerial and terrestrial scenes by subtracting session 1 from session 5 and then compared the differences. We found a significant 5-1 learning difference between aerial ($M = -259.66$, $SE = 37.46$) and terrestrial scenes ($M = -158.35$, $SE = 34.79$; $t(29) = -4.04$, $p < .001$). Taken together, these learning patterns suggest that (1) terrestrial scene learning occurred early and aerial learning continued into later training sessions, and (2) considerably more learning took place over the course of the first five sessions for aerial scenes.

Figure 3

Figure 3. a) Viewpoint gap (aerial - terrestrial) by session. b) Naturalness gap (natural - manmade) by session.

Similarly, the performance difference between manmade and natural scenes decreased over the course of the training. The average difference in performance between manmade and natural scenes was 152 ms (with an efficiency advantage for manmade scenes) at the first session, and this gap decreased to 69 ms at by the fifth session (approximately a 54% improvement; $t(29) = -6.44$, $p = .001$). The difference between manmade and natural scenes

progressed in a linear fashion ($F(4,116) = 21.53, p < 0.0001, \eta_p^2 = .42, 90\% \text{ CI } \eta_p^2 = (.297, .502)$), albeit planned comparisons between successive sessions showed significant differences only between the first and second session ($t(29) = 4.27, p < 0.0001$) and second and third session ($t(29) = 4.27, p < 0.01$), while there were no further significant changes beyond the third session of training (all p 's > 0.20)(see Figure 3b).

Finally, we observed a significant Viewpoint by Naturalness by Session three-way interaction ($F(4,116) = 3.48, p = .01, \eta_p^2 = .11, 90\% \text{ CI } \eta_p^2 = (.015, .175)$). To assess how the joint effects of Naturalness and Viewpoint vary across time, we broke down the Viewpoint effect (difference in IE between Aerial and Terrestrial) to the manmade and natural scenes and examined whether the reduction in the viewpoint gap differs between manmade and natural scenes, conducting a repeated-measures ANOVA using Naturalness and Session as factors. We found that the viewpoint gap was higher for the manmade ($M = 250 \text{ ms}, \text{SEM} = 21$) than the natural scenes ($M = 124 \text{ ms}, \text{SEM} = 11$) ($F(1,29) = 85.78, p < 0.0001, \eta_p^2 = .74, 90\% \text{ CI } \eta_p^2 = (.586, .818)$) and that the Viewpoint effect varied across the training session based on the scene's Naturalness (a significant Viewpoint by Session interaction effect: $F(4,116) = 3.48, p < .02, \eta_p^2 = .12, 90\% \text{ CI } \eta_p^2 = (.015, .175)$ (Figure 4). To examine the effect of Session on the Viewpoint gap for both levels of Naturalness, we conducted two one-way ANOVAs using Session (1-5) as a factor. The Viewpoint gap decreased as a function of training for both manmade ($F(4,116) = 10.12, p < .001, \eta_p^2 = .26, 90\% \text{ CI } \eta_p^2 = (.131, .342)$) and natural scenes ($F(4,116) = 3.73, p = .02, \eta_p^2 = .11, 90\% \text{ CI } \eta_p^2 = (.019, .184)$). However, further explorations of each level of Naturalness revealed substantial improvements in learning for the manmade scenes, but not for the natural scenes. Manmade scenes showed significant improvements in IE between every successive session (planned comparisons, all p 's < 0.05), besides the difference between the third

and the fourth session ($p < 0.76$). In contrast, in the natural scenes no significant difference was noted between any of the successive session pairs (all p 's > 0.07). In sum, memory-based improvements in generalizing from one viewpoint to another are manifest primarily for the manmade scenes and not for the natural scenes.

Figure 4

Figure 4. Viewpoint gap (aerial - terrestrial) for manmade and natural scenes by session.

Learning Transfer to Novel Scenes

We next examined whether participants which completed five sessions of training will exhibit one of the hallmarks of training, learning transfer. In a sixth session, participants performed the same category verification task with a set of completely novel exemplars of the same scene categories. We first assessed the extent to which the Naturalness and Viewpoint effects that we observed in the first five sessions extended to a novel set of images. We found similar Viewpoint ($F(1,29) = 117.22, p < 0.0001, \eta_p^2 = .80, 90\% \text{ CI } \eta_p^2 = (.669, .857)$), Naturalness ($F(1,29) = 116.03, p < 0.0001, \eta_p^2 = .80, 90\% \text{ CI } \eta_p^2 = (.667, .856)$) and interaction ($F(1,29) = 44.08, p < 0.0001, \eta_p^2 = .60, 90\% \text{ CI } \eta_p^2 = (.386, .713)$) effects. Participants

demonstrated better performance for terrestrial scenes ($M = 900$ ms $SEM = 49$) compared to aerial scenes ($M = 1072$ ms, $SEM = 58$), and better performance for natural ($M = 935$ ms, $SEM = 54$) compared to manmade ($M = 1037$ ms, $SEM = 53$) scenes. Further examining the interaction, we found the viewpoint gap was larger for manmade scenes (IE difference = 215ms) compared to natural scenes (IE difference = 130 ms; $t(29) = 6.64$, $p < 0.0001$) (Figure 5).

Figure 5

Figure 5. Session 6 (transfer) performance for manmade and natural scenes as a function of viewpoint (aerial, terrestrial).

Next, we asked whether categorizing a set of unfamiliar scenes for the first time (session 1) is different from categorizing a set of novel, unfamiliar scenes (session 6) following five sessions of training. To test this, we conducted a repeated-measures ANOVA using Session (session 1 and 6), Naturalness, and Viewpoint as factors. Overall, participants were faster and more accurate in session 6 ($M = 986$ ms, $SE = 53$) compared to session 1 ($M = 1147$ ms, $SE = 58$; a significant main effect of session, $F(1,29) = 14.68$, $p = .001$, $\eta_p^2 = .34$, 90% CI $\eta_p^2 = (.111, .507)$). Further, the effects of Naturalness (Session by Naturalness interaction: $F(1,29) = 10.89$, $p = .003$, $\eta_p^2 = .27$, 90% CI $\eta_p^2 = (.066, .453)$) and Viewpoint (Session and Viewpoint combined to

form a significant interaction, $F(1,29) = 12.7$, $p = .001$, $\eta_p^2 = .305$, 90% CI $\eta_p^2 = (.087, .480)$ significantly improved with Session. The effect of Naturalness was attenuated at session 6 (IE difference = 102 ms) compared to session 1 (IE difference = 152 ms; $t(29) = 3.30$, $p < 0.002$) and similarly, the effect of Viewpoint decreased from session 1 (IE difference = 245 ms) to session 6 (IE difference = 172 ms; $t(29) = 3.56$, $p < 0.001$). Notably, Viewpoint, Naturalness, and Session formed a significant three-way interaction ($F(1,29) = 20.35$ $p < .001$, $\eta_p^2 = .41$, 90% CI $\eta_p^2 = (.176, .568)$), suggesting that the Viewpoint and Naturalness interaction effect varied from session 1 to session 6 (Fig. 6). Although the scenes were novel to the participants in both sessions, the participant's performance gap between categorizing aerial vs. terrestrial images substantially decreased with Session, and this effect was modulated by the Naturalness of the categorized scene (Manmade scenes: $F(1,29) = 18.91$ $p < .001$, $\eta_p^2 = .39$, 90% CI $\eta_p^2 = (.159, .554)$; Natural scenes: $F(1,29) = 3.14$ $p = .09$, $\eta_p^2 = .09$, 90% CI $\eta_p^2 = (.000, .277)$). For the manmade scenes, the viewpoint gap improved significantly across sessions (IE difference: 114 ms, $t(29) = 4.35$, $p < 0.0001$), whereas the Session effect was pronouncedly smaller, and less significant for the natural scenes (IE difference: 31 ms; $t(29) = 4.35$, $p < 0.05$).

Figure 6

Figure 6. Viewpoint gap (aerial - terrestrial) for manmade and natural scenes at baseline (session 1) and the final transfer session (6). Participants categorized novel scenes in both sessions.

As a last measure of transfer of learning, we created a within-set learning average (sessions 2-5) and compared it to performance in session 6. We did not observe a significant Session effect ($F(1,29) = 1.16, p = 0.29, \eta_p^2 = .04, 90\% \text{ CI } \eta_p^2 = (.000, .194)$), which combined with findings presented above strongly suggest that participants can transfer the skills they learned during training to a novel set of scene stimuli. Interestingly, a significant three-way interaction between Session, Viewpoint, and Naturalness was observed ($F(1,29) = 5.31, p < 0.03, \eta_p^2 = .15, 90\% \text{ CI } \eta_p^2 = (.009, .341)$), but an analysis of the viewpoint gap (aerial minus terrestrial) across session broken down by Naturalness revealed that this interaction simply reflects opposing directions in the very small differences in IE over session, none of which approached significance (Manmade: IE difference = 15 ms (SEM= 14), $t(29) = 1.06, p < 0.15$; Natural: IE difference = -15 ms (SEM = 11), $t(29) = -1.32, p < 0.10$). In other words, performance with novel images is equivalent to average performance over the course of training, even when breaking it into the specific naturalness conditions. Together, these and the above analyses provide strong evidence for learning transfer, implying participants were able to generalize what they learned over the course of training to novel scene exemplars they have not encountered before.

Control Experiment

To examine whether the learning effects observed in the scene categorization training paradigm did not simply reflect the effect of repeated exposure to the scene stimuli, we included in the study a control group of participants who viewed the same scene stimuli the same number of times, across the same number of sessions (including a sixth session to assess learning transfer). The only difference between the experimental and the control group was the task.

Whereas the former actively categorized the scenes, the latter performed an orthogonal, passive fixation cross task that did not require any active involvement with the scene content (see also Hansen et al., 2018). First assessing learning during the first five sessions, we found a significant main effect of Session ($F(4,80) = 3.99, p = .04, \eta_p^2 = .15, 90\% \text{ CI } \eta_p^2 = (.029, .234)$). However, the pattern of performance over time of the control group was quite distinct relative to the experimental group (see Figure 7, cf. Figure 1). While control participants performance improved at the second session, it actually declined with each subsequent session fitting a quadratic effect ($F(1,20) = 17.48, p < .001, \eta_p^2 = .47, 90\% \text{ CI } \eta_p^2 = (.176, .629)$). In fact, performance at the fifth session ($M = 643 \text{ ms}, SE = 48.83$) did not significantly differ from baseline performance at first session 1 ($M = 562 \text{ ms}, SE = 17.07$) ($t(20) = -1.83, p = .08$)¹. As an additional evidence for the lack of any substantial scene learning effects, we did not observe any significant interaction effects with Session (either two-way or three-way, all p 's > 0.52), indicating that extraction of scene information did not vary over time.

Figure 7

¹ It is important to note there was a lot more variation in responses in the later sessions – in fact, the SEs linearly increased over the course of the training. This could potentially reflect fatigue and/or carelessness when performing the fixation cross task. Notably, this trend is not observed with the experimental group.

Figure 7. Learning trajectories across training sessions as a function of scene naturalness (manmade, natural) and viewpoint (aerial, terrestrial) for the control group.

Control participants completed the fixation cross task faster in the natural scene trials ($M = 572$ ms, $SE = 27$) compared to the manmade scene trials ($M = 590$ ms, $SE = 28$) (significant main effect of Naturalness: $F(1,20) = 150.68$, $p < .001$, $\eta_p^2 = .88$, 90% CI $\eta_p^2 = (.772, .919)$). Further, this Naturalness effect manifested differently across Viewpoint (significant Viewpoint-by-Naturalness interaction, $F(1,20) = 21.00$, $p < .001$, $\eta_p^2 = .51$, 90% CI $\eta_p^2 = (.223, .662)$). A post-hoc t-test revealed that participants performed the task significantly faster during the manmade aerial condition compared to the manmade terrestrial condition ($t(20) = -3.39$, $p < .003$)(this is, in fact, in opposite direction of the pattern observed in the experimental group), while no significant difference between aerial and terrestrial scenes was observed for the natural scenes ($t(20) = -.75$, $p < 0.46$). We interpret these effects as to likely reflect incidental difficulties in discriminating the red fixation cross from its background, primarily in the manmade terrestrial scenes.

Finally, comparing performance between the first ($M=562$ ms, $SE = 17$) and sixth session ($M = 632$ ms, $SE = 49$) also failed to yield significant differences ($t(20) = -1.45$, $p = .16$), ruling out the possibility that participants showed learning transfer effects. Taken together, these findings support the notion that the training effects observed in the experimental group are specific and reflect the nature of the categorization task, rather the simply the effect of repeated exposure to the scene stimuli.

Discussion

The current study was conducted to determine the cognitive mechanisms underlying the acquisition of expertise in aerial scene recognition, and more generally, to examine how experience (via extensive training with feedback) impacts visual scene perception. We

hypothesized that performance with real-world scenes (aerial and terrestrial viewpoints of the same place) would improve over the course of training, and that this learning will lead to the formation of expert-like changes (i.e. both at the perceptual and the semantic level) allowing generalization to novel scene exemplars. Further, we predicted that increased experience will result in a bridging of the “viewpoint performance gap” in categorizing the more difficult aerial scenes compared to the easier to recognize terrestrial scenes (Loschky et al., 2015). All three hypotheses were supported by our current data. First, we found substantial learning effects with increased inverse efficiency over the five training sessions. Notably, the learning trajectories varied based on the type of category participants learned to categorize; aerial scenes showed greater learning effects than terrestrial scenes and manmade scenes showed greater learning effects than natural scenes. In other words, the more difficult the scene is to categorize initially, the more room for improvement. Second, we found strong evidence for learning transfer, the hallmark of perceptual learning. Once the training regimen was completed, participants categorized novel scenes, which they have never been trained with, significantly better compared to their first exposure to the scenes. Moreover, performance with novel scenes was comparable to participant’s average performance across training sessions. This strongly suggests that over the course of training, participants learned to extract the diagnostic features from the scene and could apply them to categorize novel scene exemplars. Finally, the viewpoint performance gap decreased as a function of training for both manmade and natural scenes, and the ability to generalize from one viewpoint to another was manifested primarily within the manmade scenes.

The current study is, to the best of our knowledge, among the first to study how expertise in scene recognition is formed and what are its underlying characteristics. Previous research on expertise with large-scale real-world environments is focused either on the formation of

navigational skills (Weisberg & Newcombe, 2018; Wolbers & Hegarty, 2010; Woollett et al., 2009), improvements in long-term memory (Šikl et al., 2019; but see Evans et al., 2011), or changes in the top-down deployment of attention (Drew et al., 2013; Litchfield & Donovan, 2016). While these lines of research offer valuable insights, they do not directly address the question of how people acquire expertise in the perceptual categorization of real-world scenes. In that respect, two important features of our design are worth highlighting. First, by using the more difficult, less common aerial scene imagery, we were able to test the plasticity of the scene recognition system, and how it interacts with semantic memory systems. Second, by constraining the level of semantic representation, and having it associated with varying visual inputs (different viewpoints of the same place), we demonstrated that experience-based perceptual changes can emerge from general memory-based learning of scene categories, which can be generalized to scenes which participants were not trained with. This is in line with Ericsson's prominent theory of expertise (Ericsson & Kintsch, 1995) suggesting that real-world experts acquire memory skills to encode relevant information to a long-term working memory supported by highly developed semantic knowledge structures, which can be automatically retrieved to facilitate perceptual processes (e.g. scene recognition).

The current findings suggest that gaining expertise in visual scene recognition entails changes to both memory and perception, and to a large extent, enhances the interaction of these two processes; over the course of training, participants learn what are the diagnostic features in each scene category, and subsequently utilize them to categorize novel scene exemplars. This conceptualization of expertise in scene recognition resonates with Schyns' Diagnostic Recognition Framework (Schyns, 1998; Schyns et al., 1998), which posits that categorization emerges from the interaction between the available perceptual information and the observer-

based task knowledge, whose interactions give rise to cue diagnosticity. According to the diagnostic recognition framework, cue diagnosticity could explain the usage of image information subtending many recognition phenomena, including viewpoint dependence (Schyns, 1998). Our findings thus provide evidence that experience in scene recognition “...involves as much learning which cue goes with which categories as learning the [object] cues themselves” (Schyns, p. 155).

The idea presented here, that expertise in scene recognition entails interactions between the visual system and other non-visual processes, such as semantic knowledge, attention, and behavioral relevance, may explain many of the phenomena observed in diverse domains of expertise that include scene-like stimuli but do not require the “categorization” of entire scenes (e.g. taxi drivers, radiologists, image analysts). What is common to all these disparate domains is the fact that they involve changes to multiple systems, even though on the face of it, they seem to reflect primarily enhancement in visual processing. The interactive framework of visual expertise (Harel, 2016; Harel et al., 2014) suggests that visual expertise is a controlled, interactive process, rather than a purely perceptual skill. Visual expertise, according to this view, develops from the reciprocal interactions between the visual system and multiple top-down factors, including semantic knowledge, top-down attentional control, and task relevance, and it is these interactions that enable the ability to flexibly access domain-specific information at multiple scales and levels guided by multiple recognition goals (Harel, 2016; Harel et al., 2014; Harel et al., 2010; Harel et al., 2011). According to this multiple system approach, in terms of neural circuitry, extensive experience within a given visual domain should manifest in widespread neural activity beyond visual cortex, primarily in areas involved in higher-level cognitive processes. In the current context, that would imply that experience in scene recognition would involve not only the

recruitment of the core scene-selective network (see above), but also the engagement of areas involved in the formation and retrieval of semantic knowledge, such as left inferior frontal gyrus and anterior inferotemporal cortex (for a review, see Binder et al., 2009) as well as areas supporting the formation of spatial memory and navigation, such as the hippocampus (Eichenbaum & Cohen, 2014). Notably, such connections are already in existence as the scene-selective network is closely linked with these large-scale cortical networks (Epstein & Baker, 2019; Steel et al., 2020).

While the current findings offer insights into the cognitive mechanisms underlying the acquisition of expertise in aerial scene recognition, there are still open questions concerning the exact nature of the training effects observed here. First, while the current results support the idea of participants learning to recognize the diagnostic features of the categorization task, it is not entirely clear what these features are, and to what extent they vary across viewpoints and categories. In other words, it still needs to be determined what are the perceptual strategies that participants employ during training, and whether (and if so, how), these strategies change with experience. For instance, as research with radiologists and chess experts (Sheridan & Reingold, 2017) suggest, one possibility is that participants start processing the scene images locally, and transition to a global processing strategy with increasing levels of experience (the holistic model of image perception: Kundel et al., 2007)². While this account is definitely plausible, unfortunately, it is outside the scope of the current work, which focused on establishing a primary training paradigm for scene recognition. Future work is needed to determine the specific perceptual information utilized by participants for performing the task. One further consideration

² Indeed, the more fundamental question of whether scene perception (irrespective of experience) relies more on local- compared to global processing has still not been resolved. Relatedly, to what extent scene perception is more heavily dependent on high- compared to low-spatial frequency scales is also still an open question (for a review and discussion of these two questions, see Kauffmann et al., 2014).

in such an endeavor would be the potential interactions between viewpoint, the basic-level label category and the image presented. The effects of viewpoint could manifest differently for specific sub-categories within manmade- or natural- scene categories. For instance, within the manmade categories, stadiums were better recognized from an aerial perspective compared to the terrestrial perspective (probably because of their distinctive shape, e.g. diamond-shaped field within a baseball stadium), whereas bridges were extremely hard to recognize from an aerial view, compared to their terrestrial counterparts (see supplementary information for the full basic-level analyses). Thus, diagnostic scene information within superordinate categories (manmade and natural) may be category- and task-specific rather than a ‘one-size fits all’ principle of information extraction.

Further limiting our ability to address the question of the diagnostic information in scene categorization training, is the fact that our scene stimuli were presented for an extended period of time, up to 2000ms. This duration is sufficiently long to allow for several eye movements to take place, implying that we cannot rule out the contribution of spatial attention to the current effects. Indeed, changes in the top-down deployment of attention, assessed by changes in gaze behavior with training, has long been considered a hallmark of expertise in various domains, including radiology (Reingold & Sheridan, 2011), chess expertise (Sheridan & Reingold, 2014), TSA operators (Liu, Gale & Song, 2007), as well as in aviation and driving (Schrivver et al., 2008; Crundall, Underwood & Chapman, 1999). Future work is needed to tease apart the different cognitive processes, including top-down attention and semantic knowledge, which impact visual scene processing. Such work will not only determine the interplay between cognitive and perceptual processes but may also reveal how different types of interactions map onto different forms of expertise, based on specific task demands (Palmeri et al., 2004). For instance,

employing eye tracking in the current categorization paradigm will reveal the potential involvement of overt attentional strategies and how they develop with increasing levels of expertise.

A third point concerns our choice of experimental paradigm. The category verification paradigm constrains people to categorize objects in a very specific way, based on the implicit notion that our visual representations are organized hierarchically (for discussion, see Jolicoeur, Gluck, & Kosslyn, 1984; Mack & Palmeri, 2011). While this paradigm is extremely efficient in quantifying visual information as a function of such putative semantic hierarchies (Harel & Bentin, 2009), it is possible that processing of large-scale environments does not follow the same principles of object categorization (Loschky & Larson, 2010), or would manifest differently without being constrained by a verbal, semantic label. In other words, the question is whether the current paradigm captures the actual processes underlying real-world scene understanding. This point is not without merit, but it should be noted that scene understanding is actually not a single unitary process, but rather a multifaceted process, encompassing a broad range of processing factors and observer goals (Malcolm et al., 2016). Thus, we suggest that while the current focus on scene categorization might seem narrow at first, nevertheless, it allowed us to demonstrate behavioral changes as a function of training with scenes, providing evidence for plasticity in the scene recognition system. A promising direction of research will be to examine how different goals of scene understanding (recognizing the environment, searching for information within it, navigating within it, and the action it affords; see Malcolm et al., 2016) are modulated by experience, and intriguingly, how protracted experience in achieving one goal might influence the others (e.g. will a good navigator also excel at visually recognizing their surroundings).

In summary, the present study establishes the impact of experience on the scene recognition system, showing both memory and perception contribute to enhancements in categorization performance of aerial and terrestrial scenes of the same place with increasing levels of training. We thus demonstrate that people can be trained in scene recognition above and beyond their already remarkable levels of performance, and highlight the potential mechanisms underlying the putative plasticity in the scene recognition system. Viewed from above, the current findings offer new insights into how people acquire expertise in scene recognition and can be used to enhance training in various professional domains requiring visual recognition of complex real-world environments.

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