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Chapter IV. Psychophysical studies of visual object recognition

5 We want to understand the neural mechanisms responsible for visual 6 object recognition and we want to instantiate these mechanisms into 7 computational algorithms that resemble and perhaps eventually surpass human 8 performance. In order to untangle the mechanisms orchestrating visual 9 recognition and build adequate computational models, we need to define visual 10 recognition capabilities at the behavioral level. What shapes can humans recognize and when and how? Under what conditions do humans make 11 12 mistakes? How fast can humans recognize complex objects? How much 13 experience and what type of experience with the world is required to learn to 14 recognize objects?

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We can learn about visual object recognition by carefully quantifying human performance under a variety of well-controlled visual tasks. A discipline with the peculiar and attractive name of "Psychophysics" aims to rigorously characterize, quantify and understand behavior during cognitive tasks.

20 4.1. What you get ain't what you see



It is clear that what we end up perceiving is a significantly transformed version of the pattern of photons impinging on the retina. Our brains filter and process visual inputs to understand the physical world by constructing an interpretation that is consistent with our experiences. This observation seem may counterintuitive at first: our perception is a sufficiently reasonable representation of the outside world to allow us to navigate, to grasp objects, to interpret where things are going and whether a friend is happy or not. It is extremely tempting to assume that our visual system is actually capturing a perfect rendering of the outside world.

Visual illusions constitute strong examples of the dissociation between what is in the real world and what we end up perceiving. A

simple example of the dissociation between inputs and percepts is given by the blind spot. If you close one eye, there is a part of the visual field that is not mapped onto retinal ganglion cells, the spot where these cells leave the retina to form the optic nerve. It is possible to distinguish this blind spot by closing one eye, fixating on a given spot and slowly moving a finger from the center to the



periphery until part of it disappears from view (but not in its entirety which would imply that you moved your finger completely outside of your visual field).

Visual illusions are not the exception, rather they illustrate the fundamental principle that our perception is a construct, a confabulation, inspired by the visual inputs. There is a lot of information in the world that we just do not see. As a simple example, we do not perceive with our eyes information in the ultraviolet portion of the light spectrum (but other animals do). Another simple example is when we are watching a movie. A movie is nothing more than a sequence of frames, typically presented at a rate of 30

frames per second or more. Our brains do not perceive this rate and instead we interpret objects as moving on the screen.

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In addition to not being able to perceive a lot of what's happening in the real world, our brains invent a lot of information that does not exist. Consider for example, the Kanizsa triangle illustrated in Figure 4.1. We perceive a large white triangle in the center of the image and we can trace each of the sides of said triangle. Yet, those edges are composed of illusory contours: in between the edge of a pacman and the adjacent small black triangle, there is no white edge.

69 4.2. Gestalt laws of grouping

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71 One of the early and founding attempts at establishing basic principles of 72 visual perception originated from the German philosophers and experimental 73 psychologists in the late nineteenth century. The so-called Gestalt laws (in German "gestalt" means shape) provide basic constraints about how patterns of 74 75 light are integrated into perceptual sensations (Reagan, 2000). These rules arose 76 from attempts to understand the basic perceptual principles that lead to 77 interpreting objects as wholes rather than the constituent isolated lines or 78 elements that give rise to them.

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- Law of closure. We complete lines and extrapolate to complete known patterns or regular figures. An example of this is given by the famous Kanizsa triangle. Our mind creates a triangle in the middle of the image from incomplete information (Figure 4.1).
 - Law of similarity. We tend to group similar objects together. Similarity could be defined by shape, color, size or brightness (Figure 4.2)
- *Law of proximity.* We tend to group objects based on their distance
 (Figure 4.3).
- 88 Law of *symmetry*. We tend to group symmetrical images.

- 89 Law of continuity. We tend to continue regular patterns (Figure 4.4).
- Law of common fate. Elements with the same moving direction tend to be grouped.
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These laws are usually summarized by pointing out that the forms (Gestalten) are more than the mere sum of the component parts.

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96 **4.3.** Holistic processing of faces

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98 An interesting example of the processing and interpretation of a whole 99 image beyond what can be discerned from the individual components is the f 100 holistic processing of faces. Three main observations have been put forward to document the holism of face processing. First is the inversion effect (Yin, 1969; 101 102 Valentine, 1988), which describes how difficult it can be to distinguish local 103 changes in a face when it is turned upside down (this is also called the "Thatcher 104 effect" alluding to the images of Britain's prime minister originally used to 105 demonstrate the perceptual illusion). The second observation is the composite 106 face illusion: by putting together the upper part of face 1 and the bottom part of



face 2, one can create a novel face that appears to be perceptually distinct from the two original ones (Young et al., 1987). A third argument for holistic processing is the parts and wholes effect: changing a local aspect of a face distorts the overall perception of the entire face (Tanaka and Farah, 1993).

116 4.4. Tolerance to object transformations

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A hallmark of visual recognition is our ability to identify and categorize

118 119 objects in spite of large transformations in the image. An object can cast an *infinite* number 120 121 of projections onto the retina due to changes 122 in position, scale, rotation, illumination, color, 123 etc. This invariance to image transformations 124 recognition. is critical to Our visual 125 recognition capabilities would be quite 126 useless without the ability to abstract away 127 those changes.

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129 To further illustrate the critical role of 130 tolerance to object transformations in visual 131 recognition, consider a very simple algorithm



tend to assume that the dark gray circles form a line.

that we will refer to as "the rote memorization machine". This algorithm receives 132 133 inputs from a digital camera and remembers every single pixel. It can remember 134 the Van Gogh sunflowers, it can remember a picture with your face taken two 135 weeks ago on Monday at 2:30pm, it can remember exactly what your car looked like three years ago on a Saturday at 5:01pm. While such extraordinary memory 136 137 might seem quite remarkable at first, it turns out that this would constitute a 138 rather brittle approach to recognition. This algorithm would not be able to 139 recognize your car in the parking lot today, because you may see it under a 140 different illumination, a different angle, and with different amounts of dust than in 141 any of the memorized photographs. This problem is beautifully illustrated in a short story by Argentinian fiction writer Jorge Luis Borges in "Funes the 142 143 memorious", relating the story of a character who has infinite memory due to a 144 brain accident. Borges concludes: "To think is to forget differences, generalize, 145 make abstractions".

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147 Our visual system is able to abstract away many of those image 148 transformations to recognize objects. The visual system shows a significant 149 degree of robustness to changes in many image properties, including the 150 following: 151

- 152 •Scale (e.g. you can recognize an object at different sizes). You can easily 153 demonstrate the strong degree of tolerance for object transformations. 154 For example, take a piece of text with 12pt font size, hold it at arm's 155 length and focus on any given letter, say "A". The A will subtend a 156 fraction of one degree of visual angle (approximately the size of your 157 thumb at arm's length).
- 158 •Position with respect to fixation (e.g. we can recognize an object placed 159 at different distances to the fixation point)
- 160 •2D rotation (e.g. we can recognize an object after turning our head sideways or rotating the object within the plane) 161 162
 - •3D rotation (e.g. we can recognize an object from different viewpoints)
- 163 •Color (e.g. we can recognize the objects in a photograph whether it's in 164 color, sepia, grayscale)
- 165 •Illumination (e.g. consider illuminating an object from the left, right, top or 166 bottom)
- 167 •Cues (e.g. an object's shape can be determined by edges, by motion 168 cues, by completion without sharp edges)
- 169 • Clutter (e.g. we can recognize objects despite the presence of other 170 objects in the image)
- 171 •Occlusion (e.g. we can recognize objects from partial information)
- 172 •Other non-rigid transformations (e.g. we can recognize faces even with 173 changes in expression, aging, even from the line drawing sketches in 174 Figure 4.5!)

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can identify the objects in these line drawings despite the extreme simplicity in the traces and the minimal degree of resemblance to the actual objects.

A particularly intriguing example of tolerance is given by the capability to recognize caricatures and line drawings. At the pixel level, these images seem to bear little resemblance to the actual objects and yet, we can recognize them quite efficiently, sometimes even better than the real images!

4.5. Speed of visual recognition

Visual recognition *seems* almost instantaneous. Several investigators have shown that we

193 can recognize complex objects in a small fraction of a second.

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One of the original studies by Mary Potter consisted of showing a sequence of images in a rapid sequence (RSVP, rapid serial visual presentation) and showing that subjects could detect the individual images even when presented at rates of 8 per second (Potter and Levy, 1969). Complex objects can be recognized when presented tachistoscopically for < 50 ms without a mask, even in the absence of any prior expectation or other knowledge (Vernon, 1954).

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202 Part of the delays in reaction time measurements are associated with the 203 behavioral response. In an attempt to constrain the amount of time required for 204 visual recognition. Thorpe and colleagues recorded evoked response potentials 205 from scalp electroencephalographic (EEG) signals while subjects performed a 206 go/no-go animal categorization task (Thorpe et al., 1996). They found that frontal 207 cortex electrodes showed a differential signal at about 150 ms; they argued that visual discrimination of animals versus non-animals in complex scenes should 208 209 happen before that time. Kirchner et al used eye movements to elicit rapid 210 responses and showed that subjects could make a saccade to discriminate the 211 presence of a face or non-face stimulus in slightly more than 100 ms (Kirchner 212 and Thorpe, 2006). These observations place a strong constraint into the 213 mechanisms that underlie visual recognition.

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Such speed in object recognition also suggests that the mechanisms that integrate information in time must occur rather rapidly. Under normal viewing conditions, all parts of an object reach the eye more or less simultaneously (in the absence of occlusions and object movement). By disrupting such synchronous access, one can probe the speed of temporal integration in vision. In a behavioral experiment to quantify the speed of integration, Jed Singer presented different parts of an object asynchronously (Figure 4.6), like breaking



experiment. Subjects fixate and they observe a sequence of frames in which the object fragments are separated by a stimulus onset asynchrony (SOA). Subjects perform a 5-alternative forced choice categorization task. Subjects could integrate information up to asynchronies of about 30 ms.

- Humpty Dumpty and trying to put the pieces back together again. He reasoned that if there was a long interval between the presentation of different parts, subjects would be unable to interpret what the object was, but if the parts were presented very close in time, the brain would easily be able to integrate them back to a unified perception of the object.
- 227

228 Another striking example of temporal integration is the phenomenon 229 known as *anorthoscopic perception*, defined as perception of a whole object in 230 cases where only a part of which is seen at a given time, perhaps one of the very 231 earliest attempts at cinema. In classical experiments, an image is seen through a 232 slit and the image moves rapidly allowing the viewer to catch only a small part of 233 the whole at any given time. The brain integrates all the snapshots and puts them 234 together to create a perception of a whole object moving. The power of temporal 235 integration is emphasized in cases where an actor is placed in a completely dark 236 room wearing black with only a few sources of information placed along his body.

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237 With just a handful of points it is 238 possible to infer the actor's motion 239 patterns(Johansson, 1973). 240 Related studies have shown that it is possible to dynamically group 241 242 and segment information purely 243 based temporal on 244 integratoin(Anstis, 1970; Kellman 245 and Cohen, 1984).

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2474.6.Beyond pixels –248contextual effects

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250In addition to temporal251integration, visual recognition also



exploits the possibility of integrating spatial information. 252 Several visual 253 illusions demonstrate the existence of strong contextual effects in visual object 254 recognition. For example, it is significantly more difficult to recognize faces when they are upside down (see "Holistic processing" above). In a simple yet elegant 255 256 demonstration, the perceived size of a circle can be strongly influenced by the 257 size of its neighbors (Figure 4.7). Another extremely simple example is the 258 Muller-Lyer illusion: the perceived length of a line with arrows at the two ends 259 depends on the directions of the two arrows. Several entertaining examples of

260 contextual effects have been 261 reported (e.g. (Sinha and Poggio, 262 1996; Eagleman, 2001)). These 263 strong contextual dependences 264 illustrate that the visual system spatially integrates information 265 266 and the perception of local 267 features may depend on the 268 global surrounding properties.

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Such contextual effects
are not restricted to visual
illusions and psychophysics
demos like the one in Figure 4.7.
Consider Figure 4.8. What is the
object in the white box? It is



Figure 4.8. Context matters in the real world too. What is the object in the white box?

typically very hard to answer this question with any degree of certainty. Now, turn your attention to **Figure 4.9**. What is the object in the white box? This is a much easier question! Even though the pixels inside the white box are identical in both figures, the surrounding contextual information dramatically changes the probability of correctly detecting the object. These contextual effects are very fast and can be triggered by presenting even simpler and blurred version of the background information(Wu et al., Submitted). These contextual effects also

- emphasize that perception constitutes an interpretation of the input in the light ofcontext and experience.
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- 286 **4.5 The value of experience**

287 288 Our percepts are also 289 influenced by previous visual 290 experience. This observation holds 291 multiple different temporal at 292 scales. At short time scales, 293 several visual illusions show the 294 powerful effects of visual 295 adaptation. One such illusion is the 296 waterfall effect: after staring at a 297 waterfall for a minute or so, and 298 then shifting the gaze to other static 299 objects, those objects appear to be 300 moving upward. At longer time 301 scales, the interpretation of an 302 image could depend on whether



Figure 4.9. Context matters in the real world too. What is the object in the white box?

one has seen the image before. A typical example is the Dalmatian dog: for the
first-time observer the image consists of a smudge of black and white spots.
However, after recognizing the dog, people can immediately spot him the next
time. Other similar examples are Mooney images (Mooney, 1957).

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