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Framing the Rules of Perception

Hochberg Versus Galileo, Gestalts, Garner, and Gibson

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Julian Hochberg is our greatest synthesizer of theories and experimental results in the field of perception, and he has been for a half century. Moreover, his only real predecessor was E. G. Boring, who in a single volume (Boring, 1942) put together both an intellectual and rumor-filled history of the field. Hochberg never had either aspiration. Nonetheless, in what may be the largest collection of handbook chapters on perception that anyone will ever write, Hochberg’s corpus has covered all of the important ground many times in the best of historical traditions—revising and reworking the past in light of current and ongoing research and controversies.

As have many others, I have spent a good part of my intellectual life having agreements and disagreements about perception with the several Julian Hochbergs, the authors of those chapters and of various experimental works. For example, occasionally I would find myself tantalized by an idea that he had proposed several decades before, only to discover that he had disavowed it not long before I was embracing it. But Hochberg’s legacy is not continual revolution. One thread that runs through his work is a concern with the rules by which perception occurs. There can be no doubt that our perception of the world around us occurs in a very reliable and repeatable way. But why? This was Koffka’s query: “Why do we perceive things as we do?” (Koffka, 1935, p. 75). Perception is rule-governed but in what form should we express its rules? Historically, there are a number of candidates for framing an answer. Here, I will consider four.

Galileo and Descartes: Rules as Math

We can look first to Galileo and the idea of a mathesis universalis. That is, our knowledge about nature—and the mind, and hence perception—must be written in the language of mathematics (see Klein, 1985, p. 95). No field has embraced this idea more than physics, and few physicists more than Wigner (1979, p. 237), who concluded: “The miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics is
a wonderful gift which we neither understand nor deserve. We should be grateful for it and hope... that it will extend... to wide branches of learning.” Hochberg, although an undergraduate physics major, seems never to have been seriously tempted in this direction in his study of perception.

But, nonetheless, might perception be one of Wigner’s “wide branches of learning” to which math can fruitfully be applied? Are what and how we perceive best couched in math? This is not the place to review the variety of such approaches (see, for example, Cutting, 1986, 1987, 1998), but there are many and I will return to some below. Nonetheless, there are at least two reasons to doubt that any Galilean mathesis universalis will solve many problems in perception. First, unconstrained, the reach of mathematics is too broad and powerful (Cutting, 1986, p. xi). For example, mathematics has proved as equally applicable to all of astrology as it has to all of astronomy, no less to perception and the mind. So, what would we have learned? Second, most of mathematics is precise, whereas most of perception is not. As noted by Hochberg (1956, p. 404) early in his career, there are always problems of ambiguity, uncertainty, and background noise: “the degree of the inter- and intra-individual variability of the relationship between stimulus and perceptual response... as related by the task.” To be sure, ambiguity (as multistability) has been modeled with catastrophe theory (e.g., Ta’eed, Ta’eed, & Wright, 1988); uncertainty is reasonably well captured by a fuzzy logic (Massaro, 1987), and a few researchers have become interested in the fractal structure of the background noise in experimental responses (Gilden, Thornton, & Mallon, 1995; Van Orden, Holden, & Turvey, 2003). But these are not the kinds of perceptual rules that have interested Hochberg. For him, why we perceive as we do has much more to do with meaning than with math.

Descartes was also interested in a mathesis universalis, but his interest took a different turn than Galileo’s.¹ As the methodological backbone of his Rules for the Direction of the Natural Intelligence (Helden, 1610/1989), Descartes’s set of ideas was somewhat closer to what Hochberg endorses. Few of Descartes’s rules concern psychology but Rules 14 through 16 are about representation, imagination, the senses, and memory. Hochberg has never been happy with the idea of separating these (e.g., Hochberg, 1981b), nor was Descartes. Nonetheless, following a tradition from Euclid and Arabic optics, Descartes often reduced visual perception to geometry; Hochberg never took this route.

**Gestalts, Ruled by Economy**

Hochberg was deeply affected by the Gestalt revolution, and he has served as its major interpreter for a long time (e.g., Hochberg, 1957, 1998). He was the first to quantify the idea of Pragnanz, or figural goodness, as simplicity and apply it to perception (Hochberg & McAlister, 1953). Succinctly, Hochberg later characterized this as a perceptual rule: “We perceive whatever objects or scene would most simply or economically fit the sensory
pattern" (Hochberg, 1981b, p. 263). In their landmark study, Hochberg and McAlister took Kopfermann cubes (see Figure 2.2, p. 13, this volume) and counted bits and pieces of lines and their intersections, and accounted for how they were seen in two and three dimensions. Later, confronted with several of Penrose's impossible figures (e.g., Penrose & Penrose, 1958; see also Figure 8.2, p. 76, this volume), Hochberg (1962, 1968) became dissatisfied with this approach. Nonetheless, this initial work ignited several research programs in several areas.

One program was that of Leeuwenberg (1968; Leeuwenberg & Boselie, 1988), followed by various copyists (Cutting, 1981; Restle, 1979). This approach sought to account for percepts by claiming them to be the simplest among alternatives—and this idea is still very much alive (Chater & Vitányi, 2003; van der Helm, chapter 33, this volume). Indeed, it had important roots in developments from algorithmic information theory in computer science, but even these occurred well after Hochberg and McAlister. However, the problems of simplicity as applied to perception are two; First, what one perceives is not always the simplest, however "simple" be defined (e.g., Cutting, 2000; Hochberg, 1968), and second, different ad hoc sets of primitives can be rallied at any point in support of almost any calculation of simplicity (Cutting, 1987; Goodman, 1972; Hochberg, 1998). The theory is principled, but the primitives often are not. But no matter, the theory is wrong.

**Shannon and Garner to Bayes: Rules as Probabilities**

A third approach to rules for perception burgeoned in the 1950s after the information-theoretic work of Shannon (1948; Shannon & Weaver, 1949). Hochberg lived through and beyond this information revolution in psychology. With Attneave (1954), he was the first to apply aspects of these ideas to perception, as discussed in the previous section. Within the field of perception, the work of Garner (1962, 1970) was closest to Shannon's ideas of information as the reduction of uncertainty about a perceptual stimulus. There is something deeply attractive about this idea: There is more information in a stimulus if you know little about it, and less if you know a lot. Thus, if you are clueless about the day of the week, and I tell you it's Friday, you receive information (bits = log(7)); but if you already know it is Friday, you had no uncertainty and thus received no information. The problem with this approach, however, is nontrivial—knowing in advance what the perceiver knows. But one way out of this problem for Garner was that perception was fundamentally about seeking information. Hochberg has always been sympathetic with this idea.

Garner, who was one of my graduate advisors (Cutting, 1991), was also sympathetic to Bayesian statistics, and aspects of his work can be viewed as an intellectual precursor to Bayesian approaches to perception. More recently, Knill and Richards (1996) used Bayes' rule to study scenes, and
their book is the contemporary starting point for this approach. But here let me apply it to objects and information:

\[ p(\text{object} \mid \text{information}) = \frac{p(\text{information} \mid \text{object}) \times p(\text{object})}{p(\text{information})}, \quad \text{Eq}(1) \]

where \( p \) is probability and \( p(\text{object} \mid \text{information}) \) is the probability of a particular object being present given the particular information in the visual array. Recently, there have been some stunning uses of Bayes’ theorem in perception (Kersten, 1997; Weiss, Simoncelli, & Adelson, 2002), but some rather stringent constraints must be placed on the formula above. Given free rein of all possible objects and information, both the probability of any given object and of any given information source flits with zero. Thus the latter part of the equation—\( p(\text{object})/p(\text{information}) \)—can be wildly unstable. All of the real work in Bayesian approaches to perception is in the controlling of these “priors” (the a priori probabilities). Moreover, I claim that when the probabilities of these two are the same, we have something close to Gibson’s approach, discussed below.

Four decades before the popularization of Bayesian approaches to perception, however, Brunswik (1956) was interested in these very issues. He focused centrally on what came to be known as the cue validity of information and the ecological validity of experiments. For example, Brunswik was interested in the probability that any given cue (such as relative size) specified some property of objects of the world (such as their relative depth). Quite boldly in his research program, he set out to assess such probabilities, and he worried deeply about important issues such as sampling. Hochberg’s (1966) great admiration for the rigor of Brunswik, one of his own advisors at Berkeley, did not stop him from providing a withering critique. Brunswik used pictures as stimuli, and the objects in pictures have quite a different set of probabilities than do those same objects in the world. For example, faces of people have a much higher occurrence rate in photographs than they would if a camera were simply randomly pointed in any direction. Thus construed in his own terms, not only was Brunswik’s search for probabilities problematic, so were his experiments. And this same critique applies generally to Bayesian approaches today. Interestingly, it is also on this ground that Gibson took on most of midcentury perceptual theory (Gibson, 1966, 1979). Although not tempted by Brunswikian or Bayesian approaches, Hochberg has nonetheless been tantalized by likelihoods, as I will return to below.

**Gibson: Rules as Certainties**

In 1949, Hochberg arrived at Cornell University as an instructor. Gibson arrived the same year as a full professor. The two shared my department for 15 years (Hochberg, 1990), with Hochberg rising through the ranks. Indeed, the earliest explication and defense of Gibson’s emerging
theoretical position in perception was in Hochberg's work (1964). The two
had overlapping interests in many areas of perception, but perhaps most
interestingly in film. For example, both had deep fascination about how
successive shots within and across scenes were perceptually plausible—that
is, why and how they worked. Not surprisingly, Gibson was most interested
in what remained the same (invariant) across shots within a scene (Gibson,
1950, pp. 159–160; 1979, pp. 297–301). But Hochberg was interested in
what the perceiver brought to the shot transition within and across scenes
to make it interpretable, using this as a model for successive glances in the
real world (Hochberg, 1978, pp. 200–211; Hochberg & Brooks, 1996,
pp. 244–277). For Hochberg: As in film, so is the world. For Gibson: As
the world, so in film. This difference made Hochberg take the structure of
film seriously, and Gibson misinterpreted it.

For Gibson, information was present in the environment and needed
only to be picked up. For Hochberg, even if it were true, this was a state-
ment that didn't answer the important questions. The observer had to find
the information (necessitating eye movements) and have some strategy
about where to look. Moreover, the role of the experimenter was to specify
what exactly that information was. Gibson had no particular interest in the
fleshing out of this idea (see Hochberg, 1981b, 1990), although an army of
researchers over 30 years set out to find these invariants (see Cutting, 1993,
for a review). And they found some—but not all that many.

For Gibson, the information sources to be picked up were invariants. A
perceptual invariant is a concept borrowed from group theory. Any one of a
group of transformations can be applied to an object, leaving it unchanged,
and the six in the Galilean group—translations and rotations in orthogonal
dimensions x, y, and z—were obvious candidates, but changes in lighting
were also important. Early on, it looked as if invariants from projective
geometry might be useful for visual perception (Gibson, 1950, p. 153n;
Johansson, von Hofsten, & Jansson, 1980), and indeed some evidence was
found in their support (Cutting, 1986). Later, however, their scope seemed
to narrow (Niall & Macnamara, 1989; Van Gool, Moons, Pauwels, &
Wagemans, 1994). Nonetheless, the attractive thing about invariants is the
putative one-to-one relationship between information and the object it rep-
resents. Reworking and simplifying Bayes, Gibson believed:

\[ p(\text{object} \mid \text{information}) = p(\text{information} \mid \text{object}) = 1. \]  
Eq(2)

That is, the information in the visual array specified the presence of the
object under all normal conditions, and the object would always contain
that information. Note, however, that the \( p \) here is probability, not per-
ception. For Hochberg, and indeed even for Gibson (1979), the perceiver
had to explore and find the information. The richness of the real world did
not necessarily make this task easier, and it was still worth doing laboratory
experiments with specially structured stimuli. About Gibson, Hochberg felt
that "it was a great achievement to have framed plausible accounts of
accurate perception in a normal environment, but it is not therefore pointless to study anything short of that” (Hochberg, 1990, p. 751).

**Hochberg on Rules**

The perceptual rule to which Hochberg has paid the most attention over the last quarter century is sometimes known as Helmholtz’s rule, or the likelihood principle: “We perceive that object or event which would, under normal seeing conditions, be most likely to produce the pattern of sensations that we receive. To fit a perceived object or event to the sensory data in this way amounts to an unconscious inference” (Hochberg, 1981b, p. 127; see also 1981a, p. 263). Stated this way, this idea is close to a Bayesian approach to perception. But rather than being interested in the algorithm of calculating the probabilities—which drags one sideways into difficult, even arcane, frequency analyses and the shoring up of priors—Hochberg is simply interested in the fact that the mind, one’s personal history, evolutionary history, and the structure of the world all matter.

This formulation nicely deals with a number of issues. One is the backward coupling of sensory data to objects and events without stating that the sensory data need to be shared across all peoples. Thus, issues of different sensory qualities (or qualia), as are found when comparing color-normal with color-weak individuals, are not stumbling blocks. Both groups have color sensations and, although different, those sensations correspond to objects and events in the world in a rule-like fashion within a given individual. Moreover, across individuals, we also know the reasons for differential neural patterns. In this manner, the rule takes a firm stance on the mind-body problem (e.g., Fodor, 1981)—it is a materialist point of view, avoiding the problems of central-state identity (mind-brain isomorphisms) and embracing a brand of functionalism (mind-brain correlations).

This rule also nicely sets aside discussion of any differential causes attributable to nature (biological endowment) and nurture (learning). In the phrasing of this rule, the ontogeny of perception doesn’t matter. All that matters is that the senses respond in the way that they do to particular objects and events, and that they respond consistently. Similarly, perceptual differences in peoples across cultures and differences in creatures across environments can be accommodated—in both cases, the patterns of sensory data that are picked up can differ as a result of learning or endowment, and understanding both is a proper focus of perceptual research.

To be sure, there has not been universal endorsement of the likelihood principle (Leeuwenberg & Boschee, 1988). Indeed, Helmholtz’s rule does put all of the onus on consistency and hedges on anything other than a “normality” of conditions—without defining normality. But the theory stands, through Hochberg, as a touchstone that every perceptual theorist must consider. Is Hochberg right? He cannot be far wrong.
Note

1. *Mathesis universalis* was a popular idea in the 17th century and may have been first promoted by the Belgian mathematician Adrianus Romanus in his *Universae mathesis idea* of 1602 (see Heffernan, 1998, p. 97n).

References


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