blind person from early in life, the person might eventually develop the ability to interpret auditory information from unconstrained natural scenes.

Brain Plasticity

In connection with his seminal work with the tactile vision substitution system, which turned achromatic images of objects from a video camera into patterns of vibration presented to a person's skin surface, Paul Bach-y-Rita speculated that substitution of vision by touch involved a reorganization of the brain, whereby the incoming somatosensory input came to be linked to and analyzed by visual cortical areas. Though a radical idea at the time, it has recently received confirmation by a variety of studies involving brain imaging and transcranial magnetic stimulation (TMS). For example, brain imaging research has shown that the primary visual cortex is activated by Braille reading in blind people and that temporary functional lesions of the visual cortex produced by TMS interfere with Braille reading. This remapping of tactile signals into the visual cortex seems to bode well for more successful sensory substitution devices in the future. Tempering this hope is the reality that the sensory bandwidth of tactile processing is so much lower than that of vision.

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See also Braille; Cutaneous Perception; Guidance Systems for Blind People; Multimodal Interactions: Visual–Haptic; Synesthesia; Visual Disorders: Blindness

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Shape Constancy

See Constancy

Signal Detection Theory and Procedures

Nearly all reasoning and decision making takes place in the presence of some uncertainty. *Signal detection theory* provides a precise language and graphic notation for analyzing decision making in the presence of uncertainty and also shows procedures for interpreting occurrence, criterion, and possible outcomes. For example, imagine that a radiologist examines a computerized tomography (CT) scan, looking for evidence of a lung tumor. Interpreting CT images is difficult and requires a lot of training. There is some uncertainty as to what is there or not. Is that white patch a tumor? If the radiologist offers the opinion that there is no tumor and is wrong, there could be grave consequences for the patient. Then again, if the radiologist incorrectly indicates there is a tumor, the patient will undergo unnecessary further cost, testing, and stress. As described in this entry, signal detection theory provides a model of this sort of decision task, and has direct application to experiments in perception, but it also offers a way to analyze many different kinds of decision problems.

Information and Criterion

In the previous example, there are two possibilities for the patient: either the "signal" (tumor in this case) is present or absent. There are also two possible decisions: either the decision maker (the radiologist in this case) thinks he or she sees the signal (the radiologist responds "yes") or does not (the radiologist responds "no"). Thus, there are four possible outcomes. Two of these are correct: a *correct reject* (the tumor is absent and the radiologist says "no") or a *hit* (the tumor is present and the radiologist says "yes"). The other two are incorrect responses: a *miss* (the tumor is present and the radiologist says "no") or a *false alarm* (the tumor is absent yet the radiologist says "yes").

The radiologist bases his or her decision on information. For example, healthy lungs have a characteristic shape. The presence of a tumor might distort that shape. Tumors may have different image characteristics: brighter or darker, or a different texture. With proper training, a doctor learns what to look for; with more practice and training, the doctor will be able to acquire more (and more reliable) information. Running another test (e.g., magnetic resonance imaging, MRI) can also be used to acquire more information. The effect of acquiring more information is to increase the likelihood of correct outcomes (a hit or correct rejection), while reducing the likelihood of errors (a false alarm or miss).

In addition to relying on information from medical tests, the medical profession encourages doctors to use their judgment. Different types of errors are not always equal. The doctor may feel that missing an opportunity for early diagnosis may mean the difference between life and death. A false alarm, on the other hand, may result only in a routine biopsy operation. Consequently, the doctor may choose to err toward "yes" (tumor present) decisions. However, other doctors under the same circumstances may feel that unnecessary surgeries (even routine ones) are bad (expensive, stressful, etc.), so they may chose to be more conservative and say "no" (no tumor) more often. They will miss more tumors, but they will be doing their part to reduce unnecessary surgeries. And they may feel that a tumor, if there really is one, will be picked up at the next checkup. These arguments are *not about information*. Two doctors, with equally good training, looking at the same CT scan, will have the same information. But they may utilize a different *criterion*. Indeed, the same doctor might use a different criterion for different patients. For example, the criterion might be shifted toward "no" responses for a patient with a higher risk of complications from a biopsy procedure. On the other hand, the criterion might be shifted toward "yes" responses for a patient with a family history of lung cancer.

Internal Response and Internal Noise

Any measurement or test result has inherent variability; repeating the measurement will give a slightly different result. Scientists call this *measurement noise*. If a doctor acquires a large number of CT scans of a patient's lungs, one after the next, each of them will be slightly different. There are many possible sources of noise. Perhaps the patient moves or breathes differently from one scan to the next, or perhaps the patient is positioned slightly differently. Every effort is made to reduce the noise (e.g., asking patients to hold still and hold their breath), but there is no way to completely eliminate it.

When people make decisions, there is another type of uncertainty called *internal noise*. To illustrate the idea of internal noise, suppose that the doctor has a set of tumor detector neurons in his or her brain; these neurons receive visual information from the doctor's eyes and the doctor monitors the responses of these neurons. These hypothetical tumor-detector neurons will give noisy and variable responses. Neurons signal information with action potentials (also called spikes), which are small, brief changes in electrical voltage that propagate along nerve fibers. The response of a neuron is typically quantified as the number of spikes per second. After one glance at a scan of a healthy lung, a hypothetical tumor detector neuron might fire 10 spikes per second. After a different glance at the identical scan, this neuron might fire 40 spikes per second.

It is not known precisely which neurons in the doctor's brain are used to perform this task, but there is some internal state, reflected by neural activity in the brain, that determines the doctor's impression about whether or not a tumor is present. This neural activity might be concentrated in just a few neurons or it might be distributed across a large number of neurons (the average response, the sum of all responses, a difference or ratio of responses, etc.). This hypothetical brain activity is called the decision maker's *internal response* (or *decision variable*). The internal response is inherently noisy. Even when there is no signal (no tumor in this case), there will be an internal response (sometimes more, sometimes less).

Probability of Occurrence, Criterion, and Possible Outcomes

Probability is the mathematical tool for describing variability of internal responses. Figure 1 shows a graph of two hypothetical internal response curves. The curve on the left is for the *noise alone* (no tumor), and the curve on the right is for the *signal plus noise* (tumor present). The horizontal axis is labeled internal response and the vertical axis is labeled probability. The height of each curve represents the likelihood that level of internal response will occur. To be concrete, the horizontal axis could be labeled in units of firing rate (10, 20, 30, etc., spikes per second). This would mean that for noise alone (no tumor), it is most likely that the internal response would be 10 spikes per second. It is also rather likely that the internal response would be 5 or 15 spikes per second, but very unlikely that the internal response would be 25 spikes per second when no tumor is present. To remain noncommittal about what and where in the brain the internal response is, the horizontal axis has not been labeled in terms of firing rates. The internal response is in some unknown, but quantifiable, units.

The decision maker must interpret these neural signals, the internal response, and then respond "yes" or "no." The simplest strategy that the decision maker can adopt is to pick a criterion along the internal response axis, responding "yes" whenever the internal response is greater than this criterion and "no" whenever the internal response is less than this criterion. One possible criterion is indicated by the vertical line in Figure 1. The criterion line divides the graph into four sections that correspond

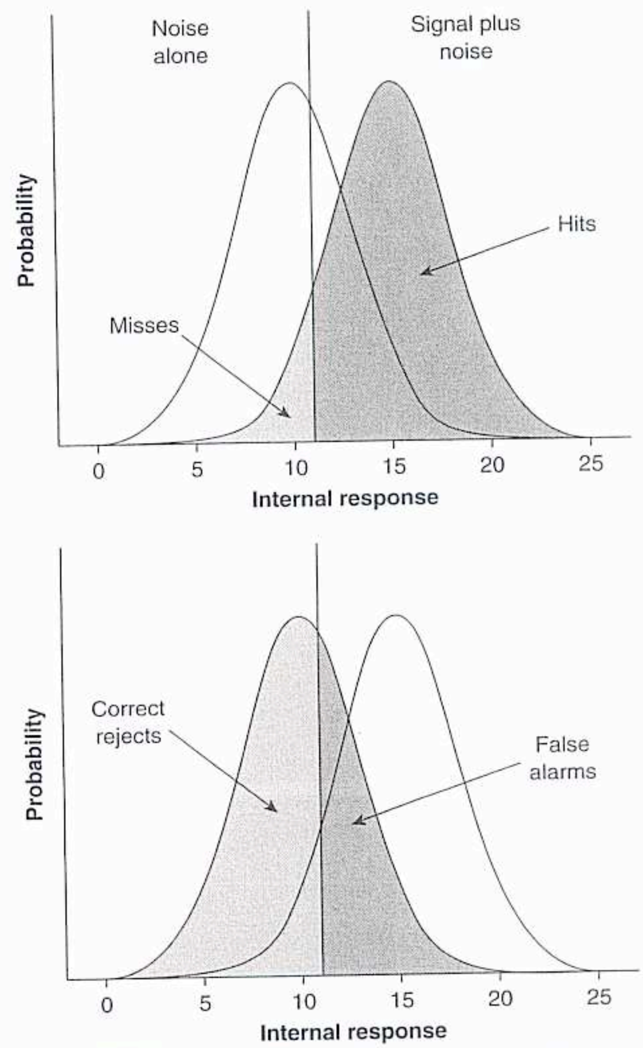

Figure 1 Internal Response, Criterion, and Possible Outcomes

Notes: Noise alone distribution (curve on left) and signal plus noise distribution (curve on right). The criterion is indicated by the vertical line. The decision maker says *yes* when the internal signal is to the right of the criterion. In the top panel, the signal is present (shaded area)—so saying *yes* above the criterion is a hit and saying *no* below the criterion is a miss. In the bottom panel, no signal is presented (shaded area)—so saying *yes* above the criterion is a false alarm and saying *no* below the criterion is a correct rejection.

to hits, misses, false alarms, and correct rejections. On both hits and false alarms, the internal response is greater than the criterion, so that the decision maker responds "yes" to these internal responses. Hits, for example, correspond to signal plus noise trials when the internal response is greater than the criterion; this is indicated in the figure as the area under the signal plus noise curve to the right of the criterion.

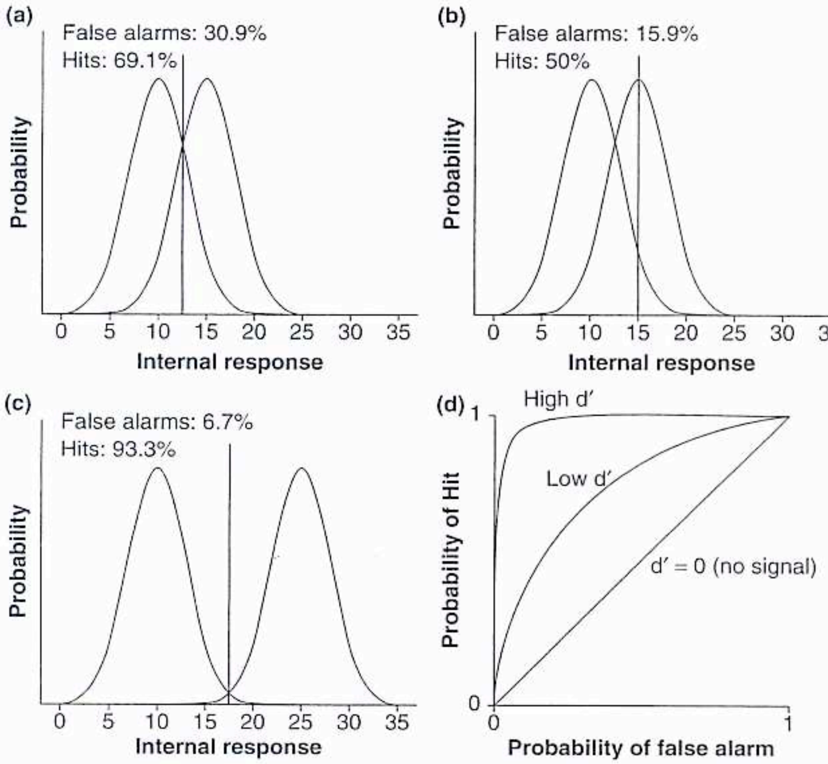

Figure 2 Discriminability and the ROC Curve

Notes: (a) Internal response and possible outcomes for the case of a symmetric criterion. (b) A higher criterion decreases the likelihood of both hits and false alarms. (c) As signal strength is increased, decision makers can reduce both false alarms and misses. (d) Receiver operating characteristic (ROC) curves for three different signal strengths (indexed by discriminability or d′) showing the combinations of hit and false alarm probabilities consistent with a given level of perceptual discriminability.

The outcome depends critically on the placement of the criterion. A symmetric criterion (Figure 2a) results in a fairly high probability of a hit (large area to the right of the criterion), but a substantial false alarm probability as well. Increasing the criterion (Figure 2b) corresponds to requiring better evidence (greater internal response) before saying "yes" (i.e., it is a more conservative criterion). The result is that a false alarm is less likely, but at the cost of reducing the likelihood of a hit as well. Thus, the position of the criterion corresponds to the decision maker's bias to say "yes" or "no."

For this case, there is no way for the decision maker to set the criterion to achieve only hits and no false alarms. The noise can never be avoided. The internal response for the signal plus noise case is generally greater but there is a distribution (a spread) of possible internal responses. Because the two curves overlap, the internal response for noise alone might exceed the internal response for signal plus noise. Because of this, the decision maker cannot always be right. The decision maker can adjust the kind of errors that he or she makes by manipulating his or her criterion, the one part of this diagram that is under the decision maker's control.

Increasing signal strength by providing more information (e.g., a better quality CT or MRI scan) makes the decision easier. This corresponds to a greater separation of the two curves (Figure 2c), allowing for an increase in the likelihood of a hit, while simultaneously reducing the likelihood of a false alarm (compare Figures 2a and 2c).

The Receiver Operating Characteristic

The full range of a decision maker's behavioral performance, for all possible settings of the criterion, can be captured in a graph, called the *receiver operating characteristic* (ROC). ROC curves (Figure 2d) are plotted with the probability of a false alarm on the horizontal axis and the probability of a hit on the vertical axis. The figure shows three examples of ROC curves, corresponding to the two signal strengths in Figures 2(a) and 2(c), as well as a signal strength of zero. Just pay attention to the middle (Low d′) ROC curve for the time being. If the criterion is very high, then both the false alarm and the hit probabilities will be very low, near the lower left corner of the ROC graph. If the criterion is very low, then both the hit and the false alarm probabilities will be very high, near the upper right corner of the graph. For an intermediate choice of criterion, the hit and false alarm probabilities will take on intermediate values. The decision maker may set the criterion anywhere, but any choice will land them with a hit and false alarm probability somewhere on the ROC curve for that particular signal strength. Notice also that for any reasonable choice of criterion and nonzero signal strength, the hit probability is always larger than the false alarm probability, so the ROC curve is bowed upward.

With more information, there is more separation between the two probability-of-occurrence curves, and the decision maker can pick a criterion to get a very high probability of a hit with almost no likelihood of a false alarm (Figure 2c). ROC curves for stronger signals bow out further toward the upper-left-corner of the graph than ROC curves for weaker signals (Figure 2d, High d′). Ultimately, if the signal is really strong (lots of information), then the ROC curve goes all the way up to the upper left corner (perfect performance with a 100% chance of a hit and no possibility of a false alarm).

The shape of an ROC curve can be summarized by a single number called the *discriminability index* or d′ (pronounced "dee prime"). The discriminability index captures the inherent difficulty of the decision maker's task, independent of his or her criterion. A hard task with only a weak signal strength yields an ROC curve near the diagonal line (Figure 2c, $d' = 0$) and an easy task with a strong signal yields an ROC curve that bends up to the upper left corner (Figure 2c, High d′). The primary virtue of d′ is that its value does not depend upon the decision maker's criterion, but instead it is a true measure of the information content in the internal response.

The decision maker's criterion will generally depend on a cost-benefit analysis of the task. For example, decision makers will typically adopt a more liberal (lower) criterion if the *payoffs* are altered to benefit "yes" answers (higher payoffs for a hit compared to a correct reject, lower penalties for a false alarm compared to a miss). This same lowering of the criterion can also happen in response to a change in the *prior probabilities* (if signal present is known to occur more frequently than signal absent). Finally, if the signal strength is increased (shifting the signal plus noise curve to the right as in Figure 2c), the decision maker will typically shift the criterion to the right, increasing the probability of a hit and decreasing the probability of a false alarm. But it is difficult to choose an optimal criterion value, and people sometimes struggle with it. When targets are extremely rare (for example, searching baggage at an airport), criteria are typically set high, resulting in a large chance of misses, despite the far higher cost of a miss as compared to that of a false alarm.

Measuring Discriminability and Criterion

In a perception experiment, signal strength is typically under the control of the experimenter, and the likelihood of a hit or false alarm is measured for each signal strength. For example, in a hearing test, a person's threshold for hearing is measured by adjusting the amplitude of a sound until it is just barely detectable. In the laboratory, the forced-choice protocol is the preferred experimental procedure. A sound is played on half of the trials, but no sound is played on the other half of the trials. The subject is forced to respond on every trial either "Yes, I heard a sound" or "No, I didn't." Because of internal noise, the subject sometimes presses the "no" and sometimes the "yes" button for the same stimulus on subsequent trials. Typically, several different signal strengths (loudnesses) are interleaved. For each signal strength, the hit rate is the percentage of signal-present trials in which the subject responded "yes." The false alarm rate is the percentage of signal-absent trials in which the subject responded "yes."

Discriminability (d′) and criterion are then estimated from the hit and false alarm rates.

With both the hit rate and the false alarm rate in hand, d′ is simply determined by noting on which of a family of ROC curves the performance lies (Figure 2d). Criterion can also be determined by where along the ROC curve the performance falls.

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See also Audition: Loudness; Auditory Thresholds

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Size Perception

See Constancy

Skin Senses

See Cutaneous Perception

Sleep and Dreams

The visual system is highly dependent on sleep for the organization of the brain and learning about the visual world. During the first year of life, one of the steepest periods of experience-dependent learning, infants sleep 70 to 80% of the time each day. Sleep deprivation during critical periods of kitten visual development produces abnormal organization of the visual cortex. These studies indicate that normal development of perception and the brain structures subserving perception are dependent on early experience and sleep. Although sleep needs changes throughout the lifespan, research shows that sleep is essential for health, memory, and restorative processes, including visual learning.

Dreams during rapid eye movement (REM) sleep are considered perceptual processes without the constraints of external stimuli. Dreams are multisensory experiences for both sighted and congenitally blind individuals. This indicates that the ability to form visual images may be independent of visual perception. This entry focuses on sleep basics, dreams and experience, visual learning and nocturnal sleep, and visual learning and naps.

Sleep Basics

To discuss the role of sleep for perception, it is helpful to introduce some basic concepts. Sleep is a highly structured set of processes separated into five stages, each demonstrating: (a) stereotypic electrical activity, (b) neurochemical expressions, and (c) both enhancement and depression in varying brain regions. The five stages (stages 1, 2, 3, 4, and REM) progress in a cycle from stage 1 through stage 4 and then to REM sleep. The duration of an entire cycle lasts for 90 to 110 minutes. Adults spend 60% of sleep in stage 2, about 20% in REM, and the remaining 20% in stages 3 and 4, which comprise slow-wave sleep (SWS). Infants spend about 50% of sleep in REM—an observation cited as evidence for the importance of REM in the developing brain. Stage 2 sleep is characterized by fast 12 to 14 hertz (Hz) waves (called spindles) and slower K complex waves. SWS consists of extremely slow brain waves, called delta waves, interspersed with smaller, faster waves. REM sleep, in contrast to SWS, is a lighter sleep accompanied by rapid irregular shallow breathing, rapid, jerking eye movements, increased heart rate, increased cortical blood flow, limb muscle paralysis, and a predominance of theta waves.

Sleep cycles vary systematically during the night. Specifically, the first part of the night is dominated by SWS. As the night progresses, a