Three methods for measuring perception

1. Magnitude estimation
2. Matching
3. Detection/discrimination

Magnitude estimation

Have subject rate (e.g., 1-10) some aspect of a stimulus (e.g., how bright it appears or how loud it sounds).

\[ P = k S^n \]

- \( P \): perceived magnitude
- \( S \): stimulus intensity
- \( k \): constant

Relationship between intensity of stimulus and perception of magnitude follows the same general equation in all senses

Steven’s power law

Matching

In a matching experiment, the subject’s task is to adjust one of two stimuli so that they look/sound the same in some respect.

Example: brightness matching

Detection/discrimination

In a detection experiment, the subject’s task is to detect small differences in the stimuli.

Psychophysical procedures for detection experiments:
- Method of adjustment.
- Yes-No/method of constant stimuli.
- Simple forced choice.
- Two-alternative forced choice
Method of adjustment

Ask observer to adjust the intensity of the light until they judge it to be just barely detectable

Example: you get fitted for a new eye glasses prescription. Typically the doctor drops in different lenses and asks you if this lens is better than that one.

Yes/no method of constant stimuli

Do these data indicate that Laurie's threshold is lower than Chris's threshold?

Forced choice

- Present signal on some trials, no signal on other trials (catch trials).
- Subject is forced to respond on every trial either "Yes the thing was presented" or "No it wasn't". If they’re not sure then they must guess.
- Advantage: We have both types of trials so we can count both the number of hits and the number of false alarms to get an estimate of discriminability independent on the criterion.
- Versions: simple forced choice, 2AFC, 2IFC

Simple forced choice:

<table>
<thead>
<tr>
<th>Four possible outcomes</th>
<th>Doctor responds &quot;yes&quot;</th>
<th>Doctor responds &quot;no&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tumor present</td>
<td>Hit</td>
<td>Miss</td>
</tr>
<tr>
<td>Tumor absent</td>
<td>False alarm</td>
<td>Correct reject</td>
</tr>
</tbody>
</table>

Information acquisition

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<tr>
<th>Doctor responds &quot;yes&quot;</th>
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**Criterion shift**

<table>
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<tr>
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**Information and criterion**

Two components to the decision-making: **information** and **criterion**.

- **Information**: Acquiring more information is good. The effect of information is to increase the likelihood of getting either a hit or a correct rejection, while reducing the likelihood of an outcome in the two error boxes.

- **Criterion**: Different people may have different **bias/criterion**. Some may choose to err toward "yes" decisions. Others may choose to be more conservative and say "no" more often.

**Internal response: probability of occurrence curves**

- **N**: noise only (tumor absent)
- **S+N**: signal plus noise (tumor present)

Discriminability (d' or "d-prime") is the distance between the N and S+N curves.

**Discriminability (d')**

\[ d' = \frac{\text{separation}}{\text{spread}} = \frac{\text{signal}}{\text{noise}} \]

**Example applications of SDT**

- **Vision**
  - Detection (something vs. nothing)
  - Discrimination (lower vs greater level of: intensity, contrast, depth, slant, size, frequency, loudness, ...)
- **Memory** (internal response = trace strength = familiarity)
- **Neurometric function/discrimination by neurons** (internal response = spike count)

**Criterion**

Distribution of internal responses when no tumor

Distribution of internal responses when tumor present

Say "no" Say "yes"
Hits: respond “yes” when tumor present

Correct rejects: respond “no” when tumor absent

Misses: respond “no” when present

False alarms: respond “yes” when absent

Criterion shift

SDT: Gaussian case

\[d' = z[p(H)] + z[p(CR)] = z[p(H)] - z[p(FA)]\]

\[c = z[p(CR)]\]

\[G(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\]

\[\beta = \frac{p(x = c | S + N)}{p(x = c | N)} = \frac{e^{-c^2/2}}{e^{-c^2/2}}\]
Receiver operating characteristic (ROC)

**ROC: Gaussian case**

- ROC curves
- $c$
- $N$, $S+N$
- $z[p(\text{H})]$, $z[p(\text{FA})]$
- $d' = 1$ (lots of overlap)
- $d' = 3$ (not much overlap)
SDT review

- Your ability to perform a detection/discrimination task is limited by internal noise.
- Information (e.g., signal strength) and criterion (bias) are the 2 components that affect your decisions, and they each have a different kind of effect.
- Because there are 2 components (information & criterion), we need to make 2 measurements to characterize the difficulty of the task. By measuring both hits & false alarms we get a measure of discriminability ($d'$) that is independent of criterion.

Measuring thresholds

- Assumptions: $x \propto$ signal strength, $\sigma$ constant

Aside: 2-IFC and Estimation of Threshold

- Frequently one wishes to estimate the signal strength corresponding to a fixed, arbitrary value of $d'$, defined as threshold signal strength.
- For this, one can measure performance at multiple signal strengths, estimate $d'$ for each, fit a function (as in the previous slide) and interpolate to estimate threshold.
- Staircase methods are often used as a more time-efficient method. The signal strength tested on each trial is based on the data collected so far, trying to concentrate testing at levels that are most informative.
- Methods: 1-up/1-down (for PSE: point of subjective equality), 1-up/2-down, etc.; QUEST, APE, PEST, ...
Staircase

Beginning point

Average of last trials

Trial

Absolute and relative thresholds

Weber's law

Relative thresholds

Absolute threshold

Difference in intensity

Gustav Fechner, c1850

Ernst Weber, c1850
Weber's law: Fechner's derivation

\[ R_1 = \log(x) \]
\[ R_2 = \log(x + dx) \]
\[ \sigma = \log(x + dx) - \log(x) \]
\[ = \log \left( \frac{x + dx}{x} \right) \]
\[ = \log \left( 1 + \frac{dx}{x} \right) \]
\[ e^\sigma - 1 = \frac{dx}{x} \]
\[ \frac{dx}{x} = k \]

Weber's law: contrast ratio derivation

\[ d' = \frac{R_2 - R_1}{\sigma} \]
At threshold: \( d' = 1 \)
\[ R_2 - R_1 = \sigma \]

**Weber's law:** To perceive a difference between a background level \( x \) and the background plus some stimulation \( x + dx \) the size of the difference must be proportional to the background, that is, \( dx = k \cdot x \) where \( k \) is a constant.

**Fechner's interpretation:** The relationship between the stimulation level \( x \) and the perceived sensation \( s(x) \) is logarithmic, \( s(x) = \log(x) \).

**Main difference:** Fechner's is an interpretation of Weber's law, a hypothesis.
**Behavioral protocol**

Two-alternative forced choice

- Fix Pt
- Dots
- Targets
- Receptive field
- Pref target
- Null target
- 10 deg
- Fixation Point
- 1 sec

**Stimulus manipulation: motion coherence**

- 0% coherence
- 50% coherence
- 100% coherence

Motion stimulus: no coherence, 50% coherence, 100% coherence

Responses of MT neurons: performed direction

**Psychometric function**

- Proportion correct vs. correlation (%)

- Britten, Shadlen, Newsome & Movshon, 1992

**Motion coherence and MT neurons**

Motion stimulus

- No coherence
- 50% coherence
- 100% coherence

Responses of MT neurons: performed direction

**Neural responses are noisy**

Each tick is an action potential

Each line corresponds to a stimulus presentation

Average across all trials

- Time (msec)
- Firing rate (sp/sec)
Perceptual decision

Decision rule: Monitor the responses of two neurons on each trial, the one being recorded and another selective for the opposite motion direction. Choose 'pref' if pref response > non-pref response.

![Graph showing probability distribution for neural responses](image)

$f_p(r)$: response PDF for pref direction  
$f_n(r)$: response PDF for non-pref direction

Probability correct

$P_{(\text{correct})} = P(r_p > r_n) = \int_{0}^{f_p(r)} f_n(r)dr$  
$\int_{0}^{f_p(r)}dr = F_p(r)$  
$P_{(\text{correct})} = \int_{0}^{f_p(r)}F_n(r)dr$

Neurometric function

$P_{(\text{correct})} = \sum f_p[r]F_n[r]$  

![Graph showing response distributions and neurometric function](image)

![Graph showing neurometric and psychometric functions](image)

Predicting the monkey's decisions

![Diagram showing the relationship between visual stimulus, neuronal response, choice probability, and behavioral judgement](image)

Shadlen, Britten, Newsome & Movshon, 1996
Predicting the monkey's decisions

Choice probability: Accuracy with which one could predict monkey's decision from the response of the neuron given that you know the distributions.

\[ f_p(r) \]: response PDF when monkey reports pref direction
\[ f_n(r) \]: response PDF when monkey reports non-pref direction

Choice probability

![Graph showing choice probability](image)

Computational model

- Noise is partially correlated across neurons.
- Responses are pooled non-optimally over large populations of neurons including those that are not the most selective.
- Additional noise is added after pooling.

![Diagram of computational model](image)

Shadlen, Britten, Newsome & Movshon, 1996