

Dimensionality

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How to Achieve High *IT*

- IT for uni-dimensional stimuli is limited
- *IT(multi-D)* is not limited by “ 7 ± 2 ”
- In general, try
 - ◆ Lots of dimensions
 - ◆ A few values (2 to 3) per dimension
 - ◆ Examples?
 - ☞ Speech perception
 - ☞ Face recognition

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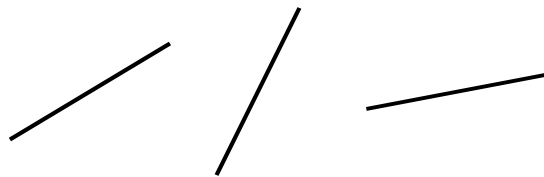
How do you define dimensionality?

- From literature – never explicitly defined
- Read between lines – number of independently manipulated physical variables
- But physical and perceptual dimensionality may not be the same!!

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Dimensionality – a Visual Example

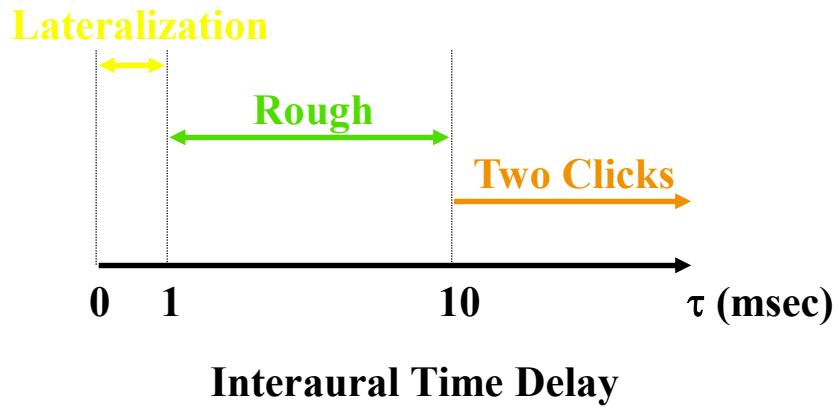


- Orientation of lines: 1D or 2D?
- IT for direction, or angle of inclination is 3.3 bits for a 5-sec exposure time (ref. p. 86, Miller's 7 ± 2 paper)
- This is clearly at the high end of 7 ± 2 ($2^{3.3}=9.8$)

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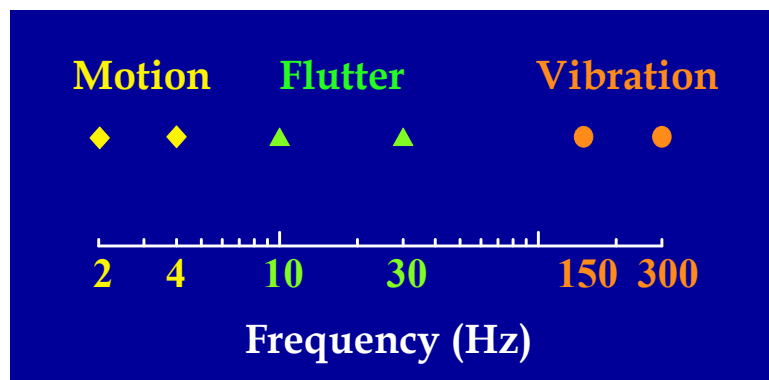
Dimensionality – an Auditory Example



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Dimensionality – a Haptic Example



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IT and Channel Capacity **For Different Sensory Modalities**

- *AL* and *DL* are in modality-specific physical units
- *IT* and *channel capacity* are in bits:
We can compare apples with oranges!

Cumulative d' and its Relationship to IT

Overview

- Based on two papers:
“Intensity perception I & II,” by Durlach & Braida
(*Journal of the Acoustical Society of America*, 1969 & 1972)
- Goal:
Towards a theory for interpreting the relation between our ability to discriminate between two intensities that differ only by a small intensity increment, and our inability to identify an intensity from among a large set of intensities that differ by very large increments (the 7 ± 2 phenomenon)

The Formal Theory

- Decision model
- Internal-noise model
 - ◆ Quantifies M and σ in the decision model in terms of sensory and memory noise
 - ◆ Sensory noise is mainly due to the subject's inability to maintain the *image* or the *trace* of the sensation precisely
 - ◆ Memory noise is due to the subject's inability to remember the general context of sounds in the experiment, and the inability to determine or represent the relation of the sensation to this context precisely.

Decision Model Revisited

$$d' = \frac{M_2 - M_1}{\sigma}$$

- Assume that Weber's Law holds, then

$$M_i = K \cdot \log I_i \quad (i=1, 2)$$

- Assume that the variance σ^2 is the sum of sensory noise β^2 (independent of I), and memory noise $G^2 R^2$ where G =constant, $R=\log(I_{\max}/I_{\min})$, i.e.

$$\sigma^2 = \beta^2 + G^2 R^2$$

- It follows that

$$d' = \frac{K \log(I_2/I_1)}{\sqrt{\beta^2 + G^2 R^2}} = \frac{\log(I_2/I_1)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}}$$

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Resolution in One-Interval Paradigms

$$d' = \frac{\log(I_2/I_1)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}} = d'(I_2; I_1)$$

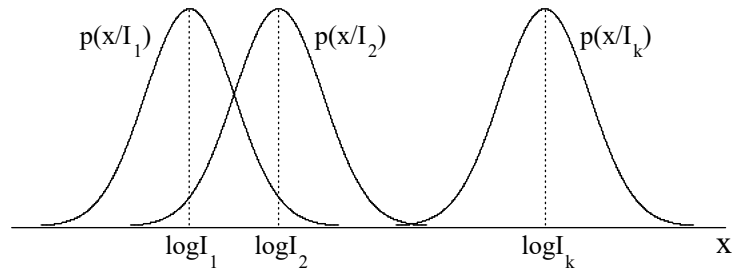
Can be extended to a wide variety of one-interval experiments, including the discrimination and absolute identification paradigms, to measure the sensitivity index between **any** pair of stimuli I_i and I_j :

$$d'(I_i; I_j) = \frac{\log(I_i/I_j)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}}$$

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d' in AI Experiments



- Sensitivity index d' is additive

$$d'(I_3; I_1) = d'(I_2; I_1) + d'(I_3; I_2)$$

i.e.,

$$\frac{\log(I_3/I_1)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}} = \frac{\log(I_2/I_1)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}} + \frac{\log(I_3/I_2)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}}$$

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Cumulative d' Links 1I-2AFC and AI Experiments

- Cumulative d' , or total sensitivity, can be expressed as:

$$\Delta' = d'(I_{\max}; I_{\min}) = d'(I_k; I_1) = \frac{\log(I_k/I_1)}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}}$$

or equivalently,

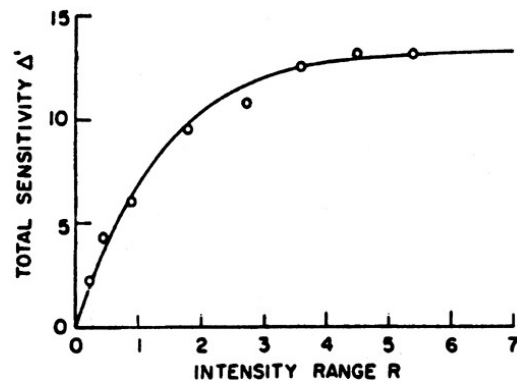
$$\Delta' = d'(I_{\max}; I_{\min}) = \frac{R}{\sqrt{(\beta/K)^2 + (G/K)^2 R^2}}$$

- Cumulative d' is a function of R only!
- When R is large, $\Delta' \approx K/G$ (i.e., constant)!

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Cumulative d' vs. R

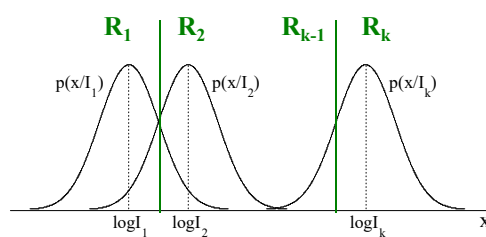


- Circles: experimental data
- Curve: derived with $K/G=13.7$ and $K/\beta=8.1$

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Predicting IT from Δ'

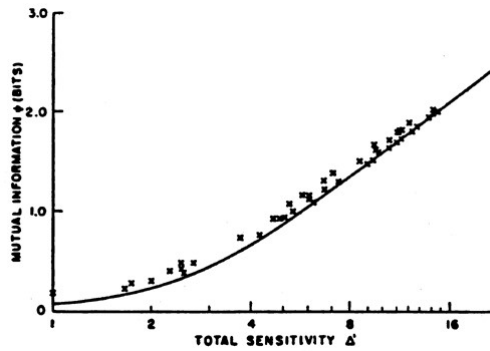


- Assumptions
 - ◆ The means of the density functions on the decision axis are equally spaced
 - ◆ The number of responses equals the number of stimuli
 - ◆ The response criteria are placed midway between adjacent means
- The stimulus-response confusion matrix can be predicted

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IT vs. Cumulative d'

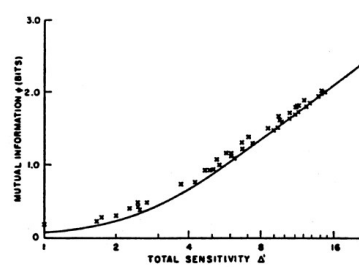
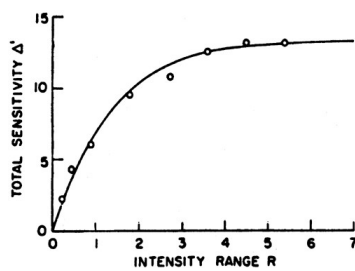


- Crosses: one subject, AI experiments with $N=10$
- Curve: theoretical prediction

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A New Interpretation of “7±2”



- Maximum $\Delta' \cong 12-15$
(estimated from experimental data)
- Therefore, *IT* for intensity is limited.

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Further Readings

- N. I. Durlach and L. D. Braida, “Intensity perception I. Preliminary theory of intensity resolution,” *The Journal of the Acoustical Society of America*, vol. 46, pp. 372–383, 1969.
- L. D. Braida and N. I. Durlach, “Intensity perception II. Resolution in one-interval paradigms,” *The Journal of the Acoustical Society of America*, vol. 51, pp. 483–502, 1972.