

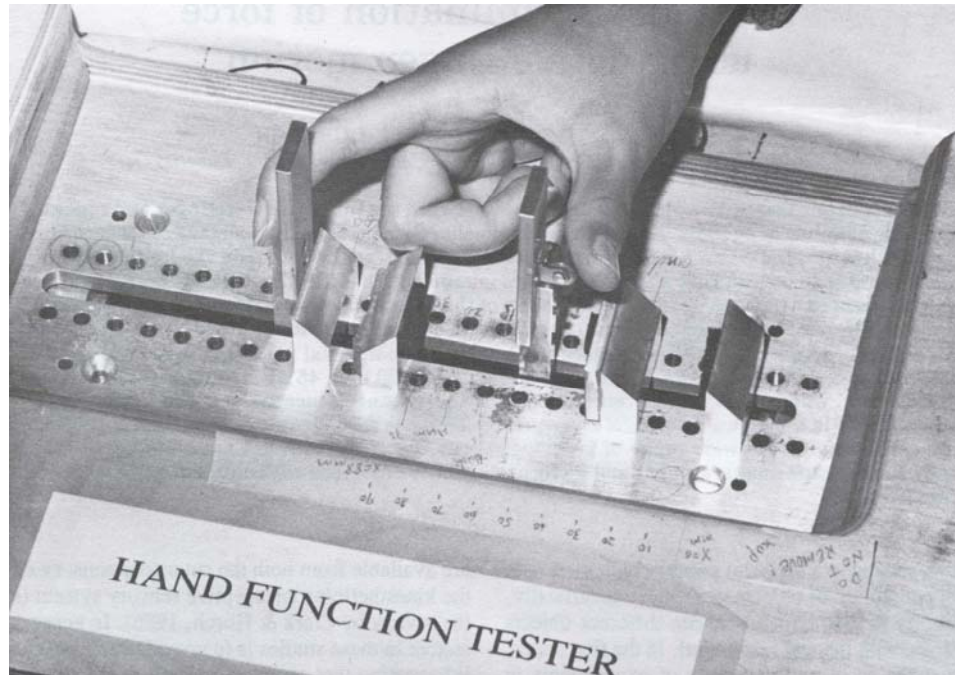
A Decision Model for Psychophysics

(Cont.)

- 1. How to Test the Decision Model**
- 2. Relating d' to DL**
- 3. Estimation of $\sigma_{d'}$**

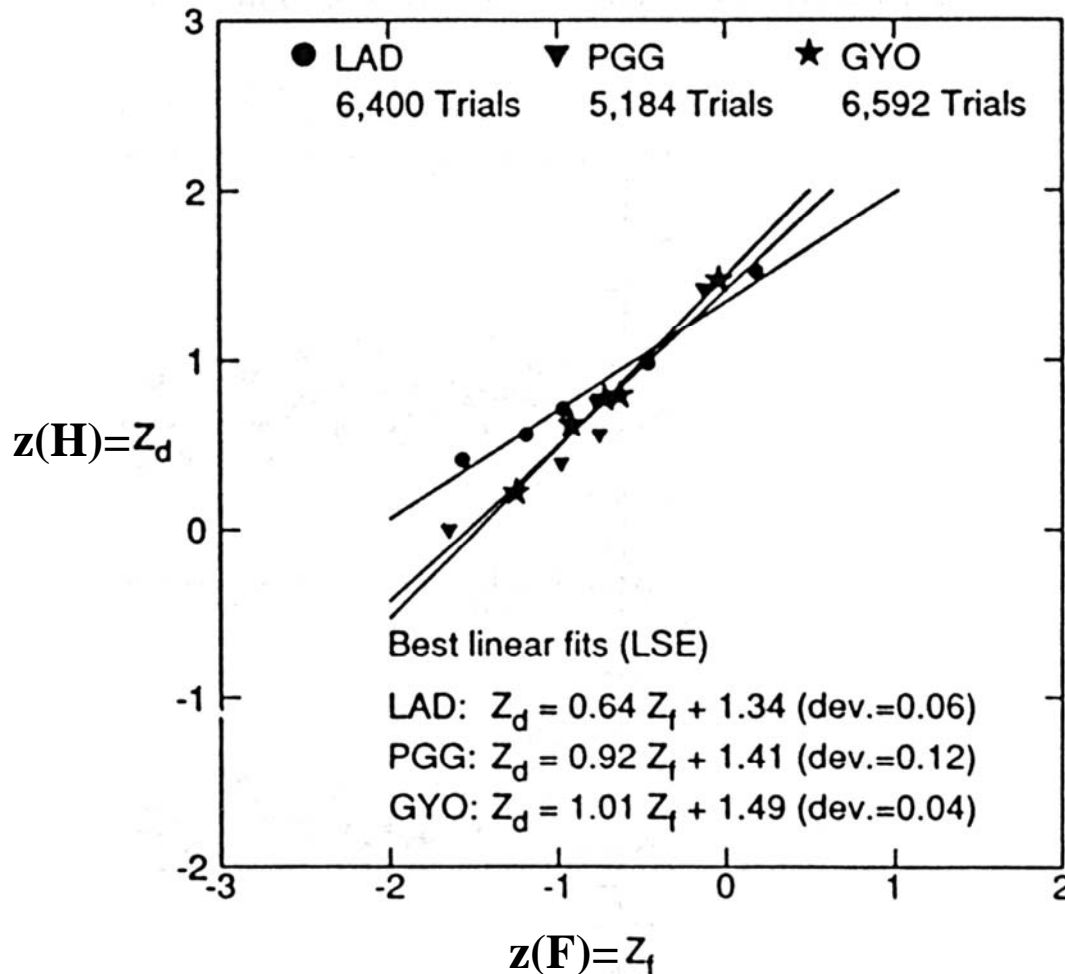
How to Test the Decision Model? — the Idea

- Pang, Tan and Durlach (1991)
- A study of manual force discrimination
- **Q: Is ROC a straight line with slope of 1?**
- Approach: Measure isosensitivity curve by using $P(S_1)=1/10, 3/10, 5/10, 7/10$ and $9/10$.



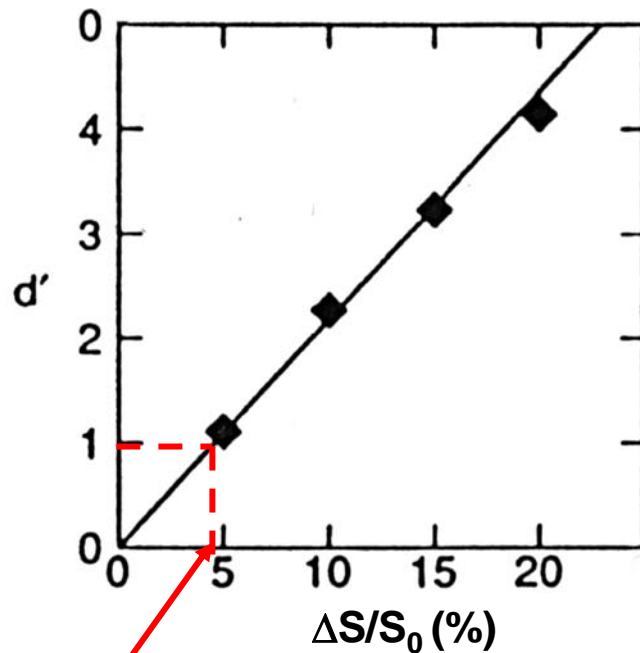
- **Apparatus: A Linear Force Grasper**
- **Stimuli: $S_1 = 5 \text{ N}$, $S_2 = 5.5 \text{ N}$**
- **Responses: “smaller” or “larger” force**

How to Test the Decision Model? — the Results



**Difference Threshold DL ,
Sensitivity Index d' ,
Just Noticeable Difference JND ,
and their Relationship**

JND



JND

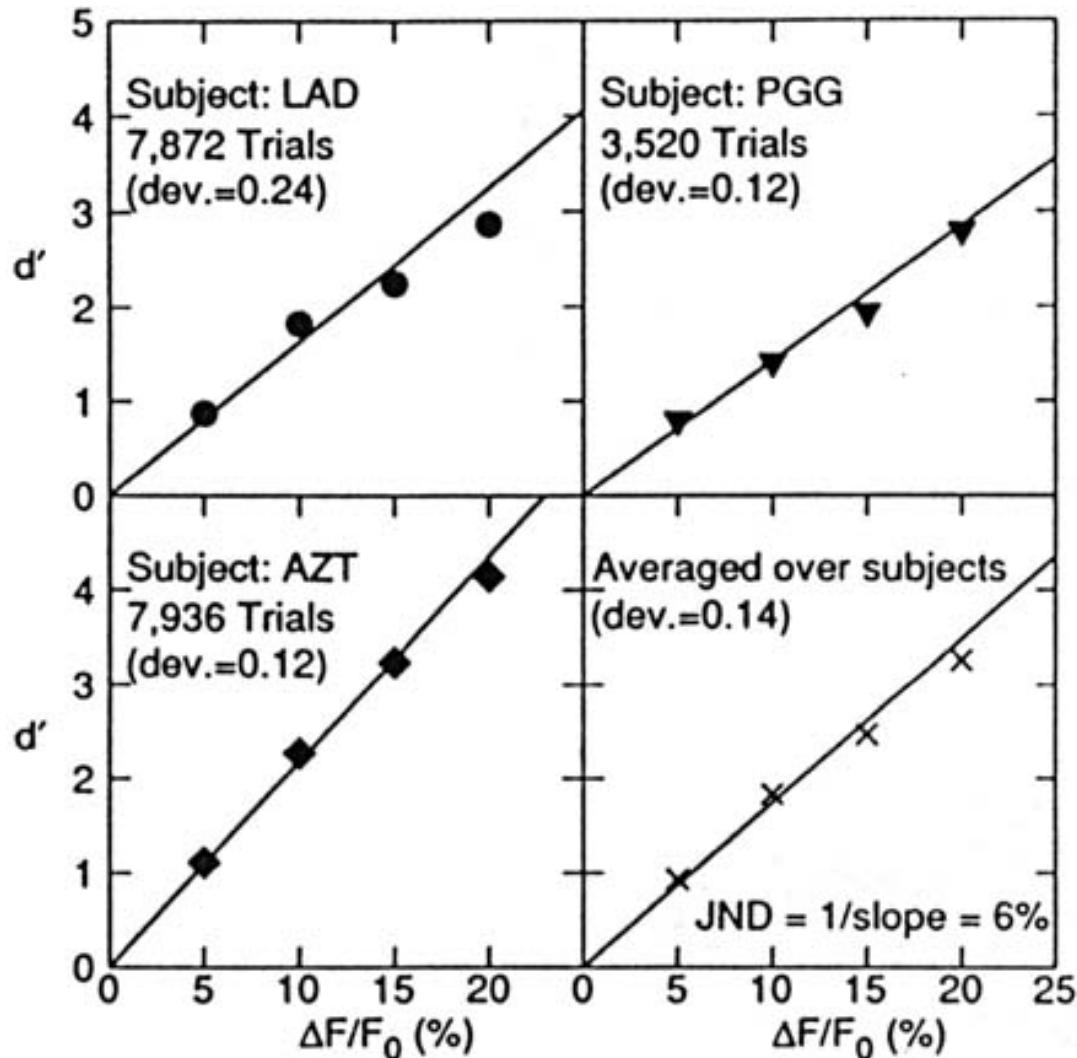
- **Just-Noticeable-Difference**
- **JND = AL (detection) or DL (discrimination)**
- **It is defined as**
$$\text{JND} = \frac{1}{\bar{\delta}}$$
- **$\bar{\delta}$ is the average of $d' / (\Delta S / S_0)$ over several values of ΔS for a given S_0**
- **($S_1 = S_0$, $S_2 = S_0 + \Delta S$)**

Estimating DL from d'

- From a 1-I experiment, we get d'
- In theory, DL can simply be computed as $DL = \Delta S / d'$
- However, estimating DL from one pair of $(\Delta S, d')$ values is not reliable
- In practice, draw d' vs. ΔS for many pairs of $(\Delta S, d')$, then compute DL as the inverse of the $d' = \Delta S / DL$ slope.
- DL is the same as JND in a discrimination exp.
 - ◆ Be very careful with units (pixel, gram, vs. %)
 - ◆ Be aware of the reference signal level S_0

Real Data

From Pang, Tan & Durlach (1991)



Legend:

$$S_1 = F_0 = 5 \text{ N}$$

$$S_2 = F_0 + \Delta F$$

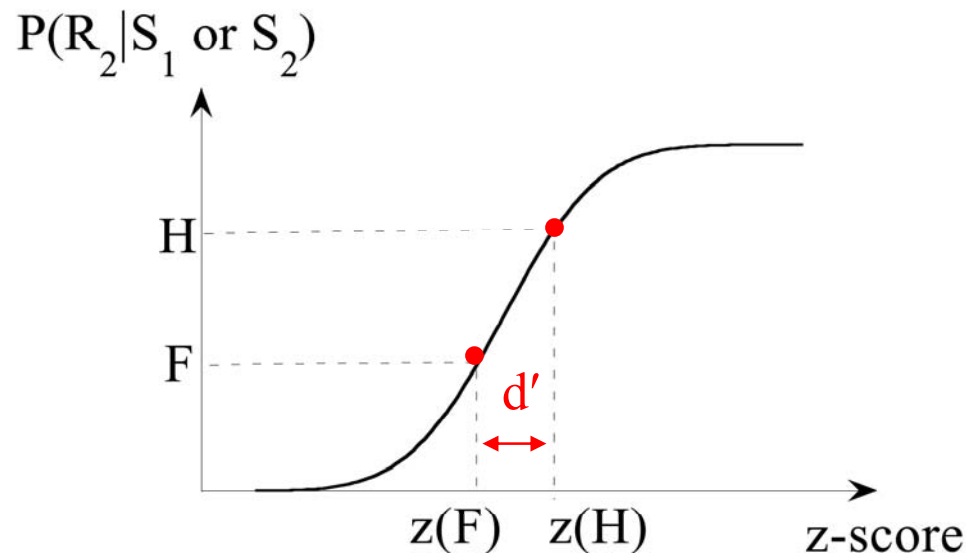
$$\Delta F/F_0 = \Delta S/S_1$$

← **JND**

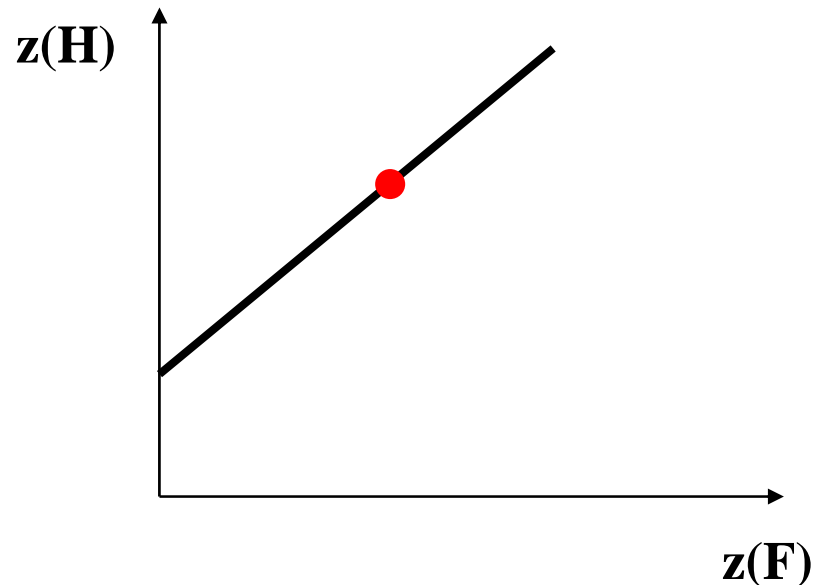
Estimation of σ_d'

The Problem

- $\sigma_{d'}$ can not be estimated directly from 1-I or 2-I experiments
- We can always find a cumulative Gaussian curve that goes through 2 points **EXACTLY**



- We can always find a straight line that goes through 1 point **EXACTLY**



- *Therefore, we can NOT measure the goodness of fit in either case with rms error*

Two Ways to Estimate σ_d'

- 1. When you only collect one pair of (H, F)
 - ◆ Need assumptions to estimate σ_d'
- 2. When you measure multiple pairs of (H, F)
 - ◆ Use the rms error of ROC curve fitting
 - ◆ There are two ways to estimate ROC
 - ☞ Run multiple experiments. Ask subjects to use different k in different sessions.
 - or*
 - ☞ Rating paradigm. Ask subjects to maintain multiple k in the same session.

The Main Idea

- Given that

$$d' = z(H) - z(F)$$

- We have

$$\sigma_{d'} = \sqrt{\sigma_{z(H)}^2 + \sigma_{z(F)}^2}$$

- Therefore, to estimate $\sigma_{d'}$, we need to estimate $\sigma_{z(H)}$ and $\sigma_{z(F)}$ first.

Method 1: Estimate $\sigma_{d'}$ with One Pair of (H, F) Values

■ Assumptions

- ◆ The only source of variability in d' is sampling error (therefore we are getting a lower-bound estimate)
- ◆ Binomial distribution approximates Gaussian with sufficient number of trials. This is true if
 - ☞ p (probability of responding “yes”) is not extreme; or
 - ☞ N (number of trials) is large when p is extreme

- It then follows that the variability of H and F are:

$$\sigma_F = \sqrt{\frac{F(1-F)}{N_1}}$$

$$\sigma_H = \sqrt{\frac{H(1-H)}{N_2}}$$

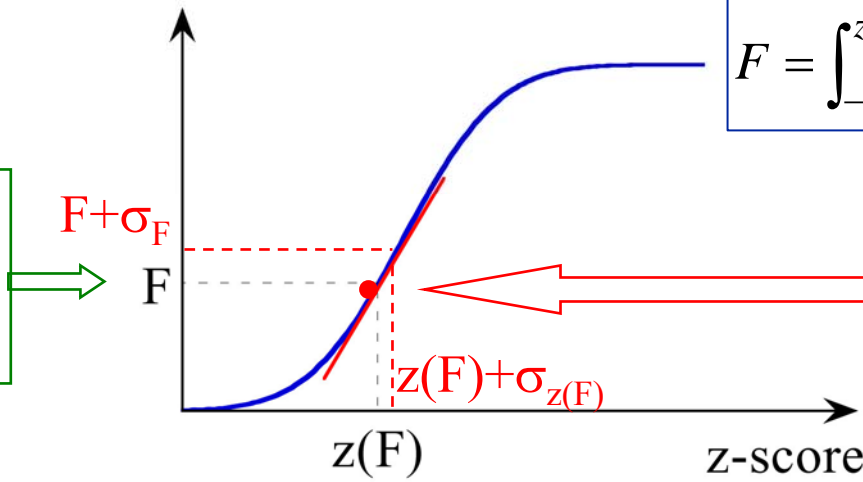
where N_1 or N_2 is the number of times stimulus S_1 or S_2 has been presented, respectively.

- All we need to do now is to estimate $\sigma_{z(H)}$ and $\sigma_{z(F)}$.

$P(R_2 | S_1 \text{ or } S_2)$

$$F = \int_{-\infty}^{z(F)} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx$$

$N(F, \sigma_F^2)$
from
assumptions



$F = \alpha \cdot z(F) + \beta$
(α, β : constants)
 $\sigma_F = \alpha \cdot \sigma_{z(F)}$

$N[z(F), \sigma_{z(F)}^2]$
based on local
linear approximation

$$\alpha = \frac{\partial F}{\partial z(F)} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}[z(F)]^2}$$

$$\therefore \sigma_{z(F)} = \alpha^{-1} \cdot \sigma_F = \sigma_F \cdot \sqrt{2\pi} \cdot e^{\frac{1}{2}[z(F)]^2}$$

Summary of Method 1

$$\sigma_{z(F)} = \sigma_F \cdot \sqrt{2\pi} \cdot e^{\frac{1}{2}[z(F)]^2} = \sqrt{\frac{2\pi F(1-F)}{N_1}} \cdot e^{\frac{1}{2}[z(F)]^2}$$

$$\sigma_{z(H)} = \sqrt{\frac{2\pi H(1-H)}{N_2}} \cdot e^{\frac{1}{2}[z(H)]^2}$$

$$\text{Finally, } \sigma_{d'} = \sqrt{\sigma_{z(H)}^2 + \sigma_{z(F)}^2}$$

It should be clear that $\sigma_{d'}$ is inversely proportional to N_1 and N_2 !

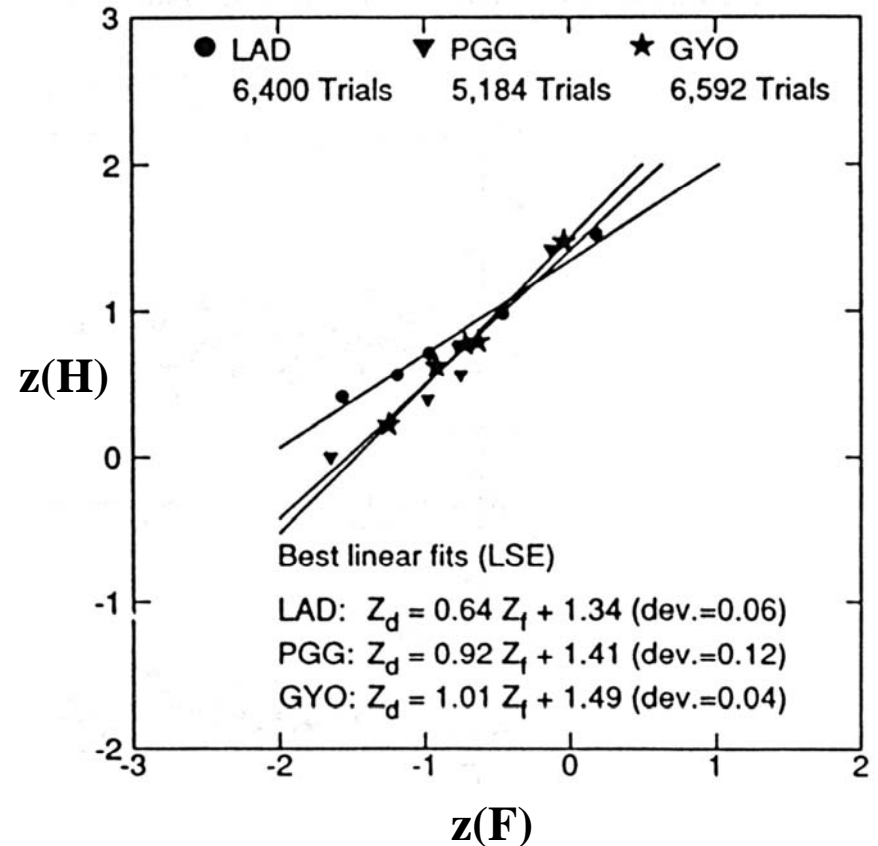
Method 2: Estimate $\sigma_{d'}$ with ROC

- No explicit assumptions are needed
- Estimate $\sigma_{z(H)}$ and $\sigma_{z(F)}$ as the rms error of straight line fitting

How??

- Then compute

$$\sigma_{d'} = \sqrt{\sigma_{z(H)}^2 + \sigma_{z(F)}^2}$$



Two Ways of Obtaining ROC

- **Multiple sessions with different k values**
 - ◆ **see Pang et al. 1991**
- **Same session with multiple k values**
 - ◆ **Rating Experiment**

Reading

- **Pang, Tan and Durlach, “Manual discrimination of force using active finger motion,” *Perception & Psychophysics*, 49(6), 531–540, 1991.**