

THEORIE DE LA DETECTION DU SIGNAL

La Théorie de la Détection du Signal (TDS) est à la fois un instrument de mesure de la performance* et un cadre théorique dans lequel cette performance est interprétée du point de vue des mécanismes sous-jacents.

En tant que telle, la TDS peut être regardée comme étant à la base de la psychophysique moderne. Le cours développera les bases de la TDS, discutera sa relation avec les concepts de seuil sensoriel et de décision et exemplifiera son application dans des situations expérimentales allant depuis le sensoriel jusqu'au cognitif.

*Signal Detection Theory is a computational framework that describes **how to extract a signal from noise, while accounting for biases and other factors that can influence the extraction process**. It has been used effectively to describe how the brain overcomes noise from both the environment and its own internal processes to perceive sensory signals (from **Gold & Watanabe (2010). Perceptual learning. Current Biol., 20(2)** R46-R48).

SIGNAL DETECTION THEORY AND PSYCHOPHYSICS

David M. Green & John A. Swets

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DETECTION THEORY

A User's Guide



Neil A. Macmillan
C. Douglas Creelman

Detection Theory: A User's Guide

(2nd edition)

NEIL A. MACMILLAN
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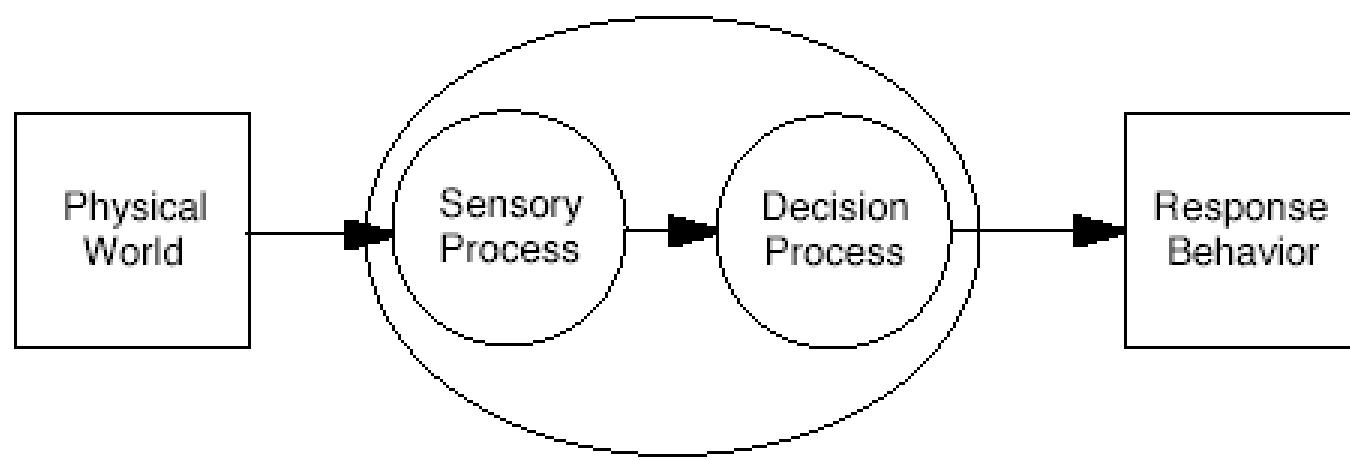
and

C. DOUGLAS CREELMAN
University of Toronto

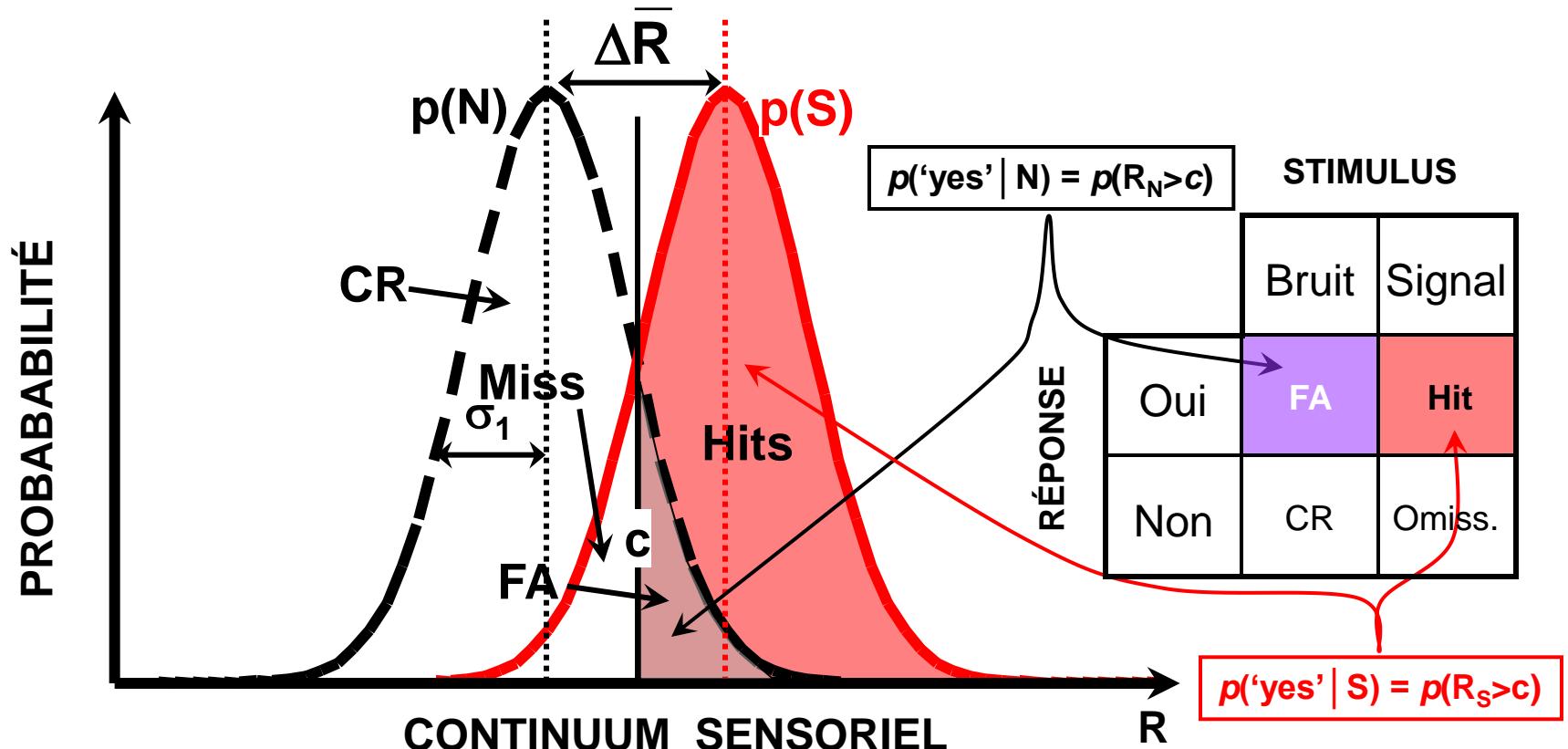


2005

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Mahwah, New Jersey London

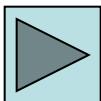


LE MODEL STANDARD : THEORIE de la DETECTION du SIGNAL



$$d' = \frac{S}{B} = \frac{\Delta \bar{R}}{\sigma} \Rightarrow z(\text{Hits}) - z(\text{FA})$$

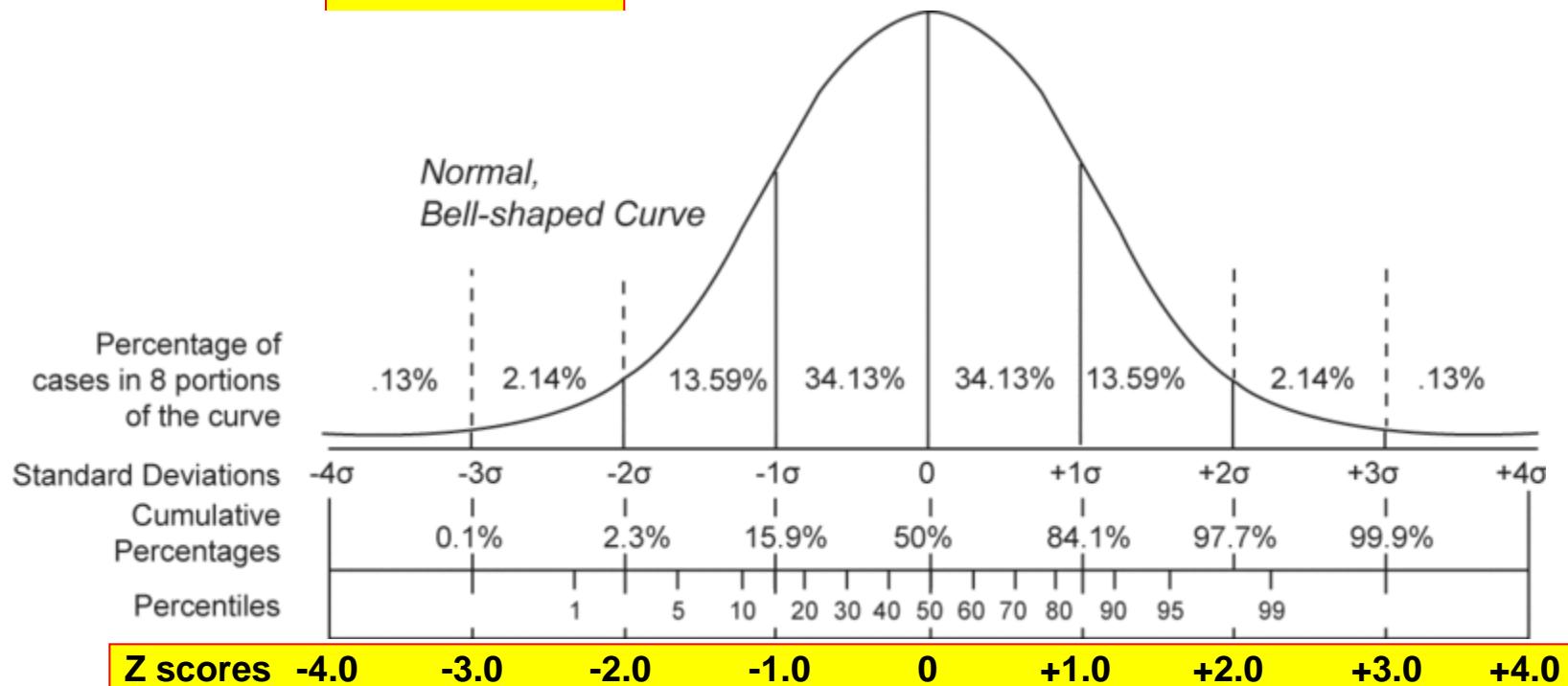
$$c_0 = -.5[z(\text{H}) + z(\text{FA})]; \quad c = z(\text{FA})$$



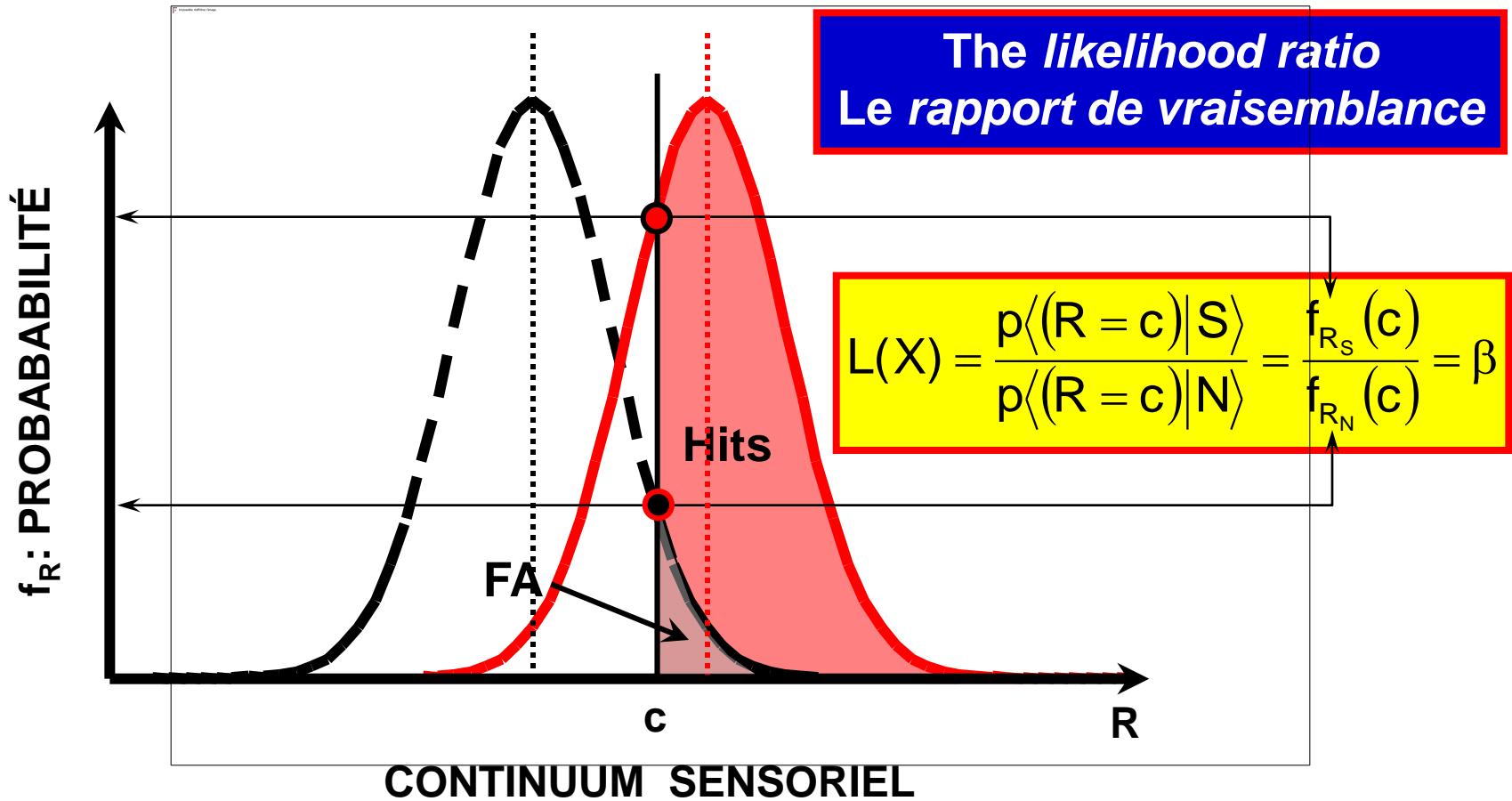
Score z

Ou « score normal » ou « score standard »

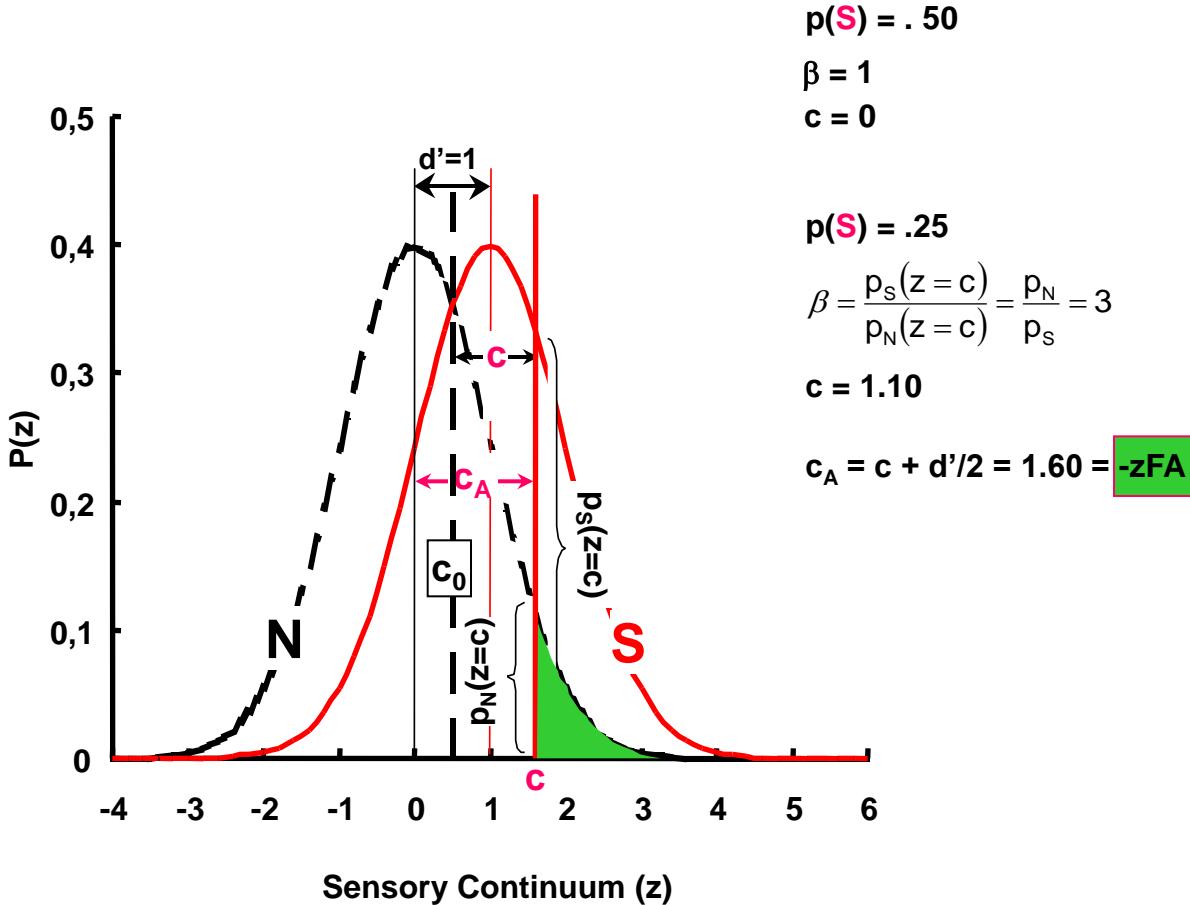
$$Z = \frac{X - \mu}{\sigma}$$



LE MODEL STANDARD : THEORIE de la DETECTION du SIGNAL

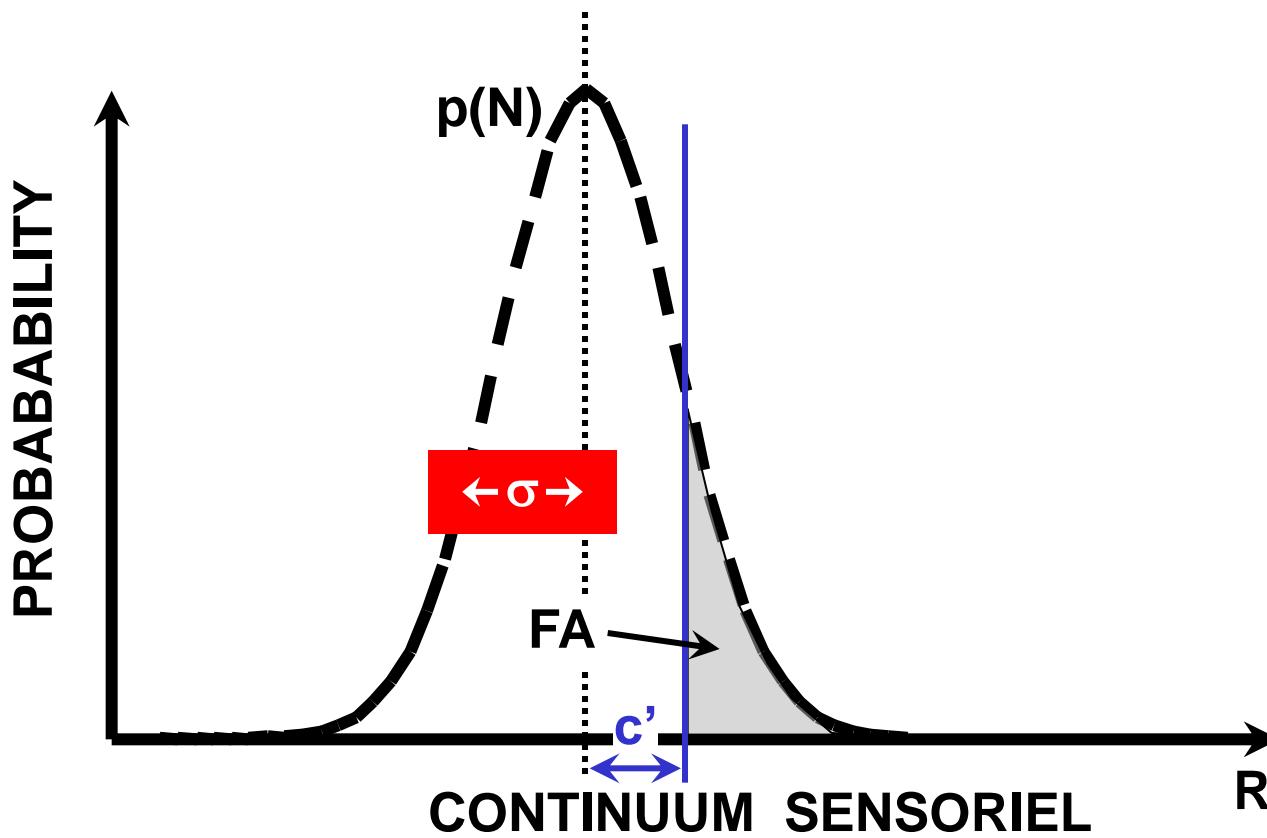


LE MODEL STANDARD : THEORIE de la DETECTION du SIGNAL



THE STANDARD MODEL: SIGNAL DETECTION THEORY

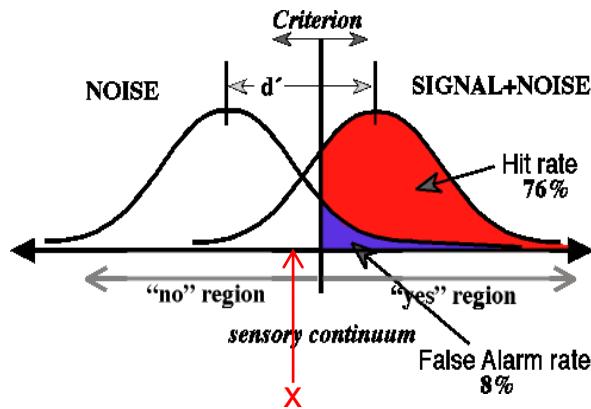
Criterion: the border between seen and not-seen



$$\xrightarrow{\quad} c' = -z(FA) \xrightarrow{\quad} c' \Rightarrow \text{in } \sigma \text{ units!}$$

Criterion setting

- Observers set a criterion that attempts to minimize the total error rate ($p_{\text{Miss}} + p_{\text{FA}}$).



- For equally probable Signal and Noise, choose S and not N when

$$p(x|S) > p(x|N)$$

i.e. when the likelihood ratio

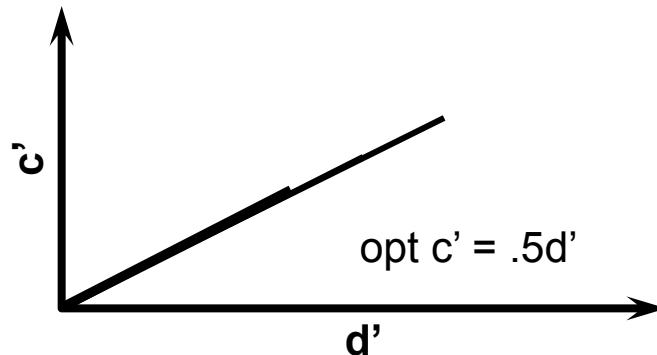
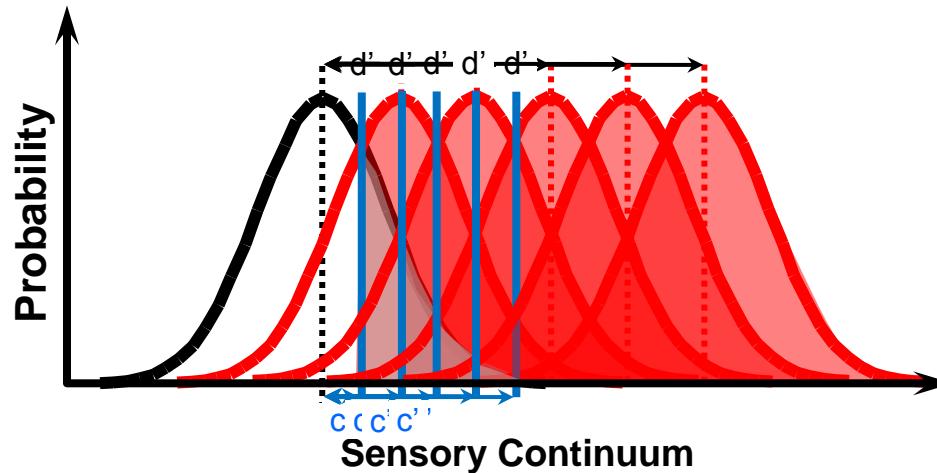
$$\beta = p(x|S) / p(x|N) > 1$$

- For unequal probabilities of S and N, $p(S)$ and $p(N)$, optimal β

$$\beta = p(N) / p(S)$$

THE STANDARD MODEL: SIGNAL DETECTION THEORY

Criterion: the border between seen and not-seen



Measured vs. Optimal criterion (β)

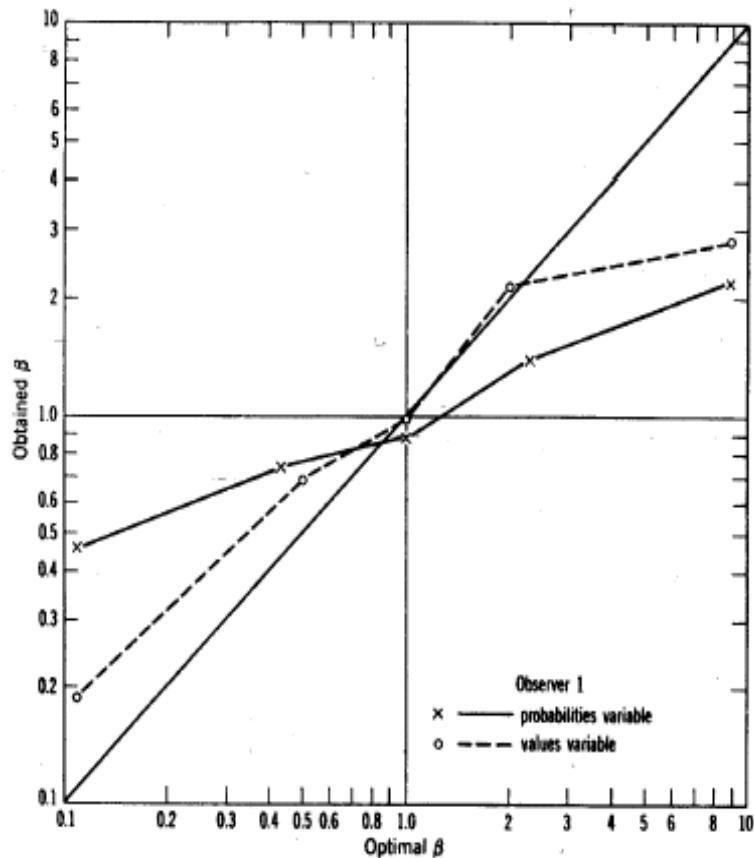
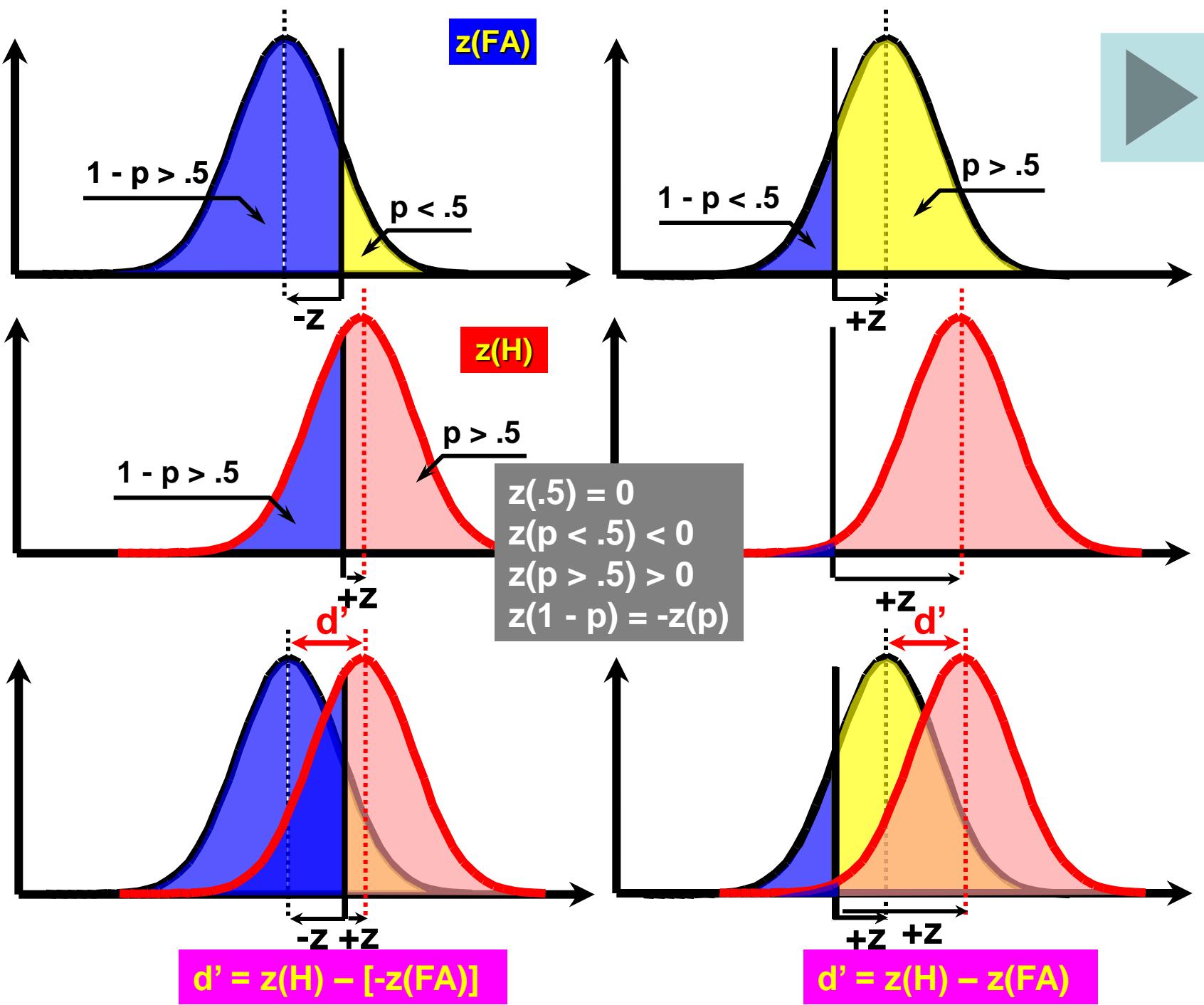


FIG. 4-3 Relationship between obtained and optimal decision criteria.

Observers are close to optimal for $p(S) = p(N)$ but become more and more suboptimal with the increasing difference between $p(S)$ & $p(N)$

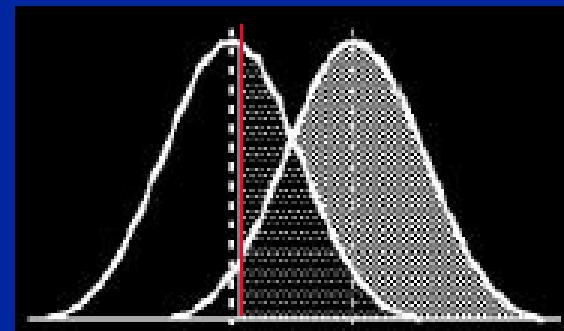


Signal detection theory: criterion effects

90%
Signal
Rate

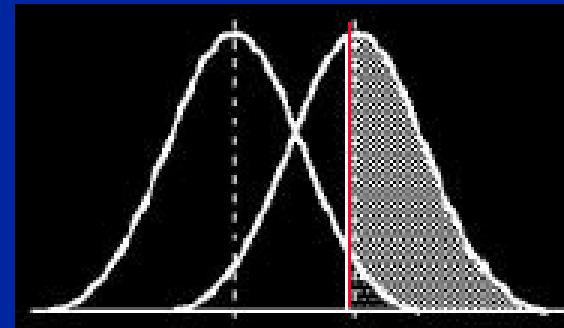
		Response	
		Yes	No
Signal	On	Hits 0.85	Misses 0.15
	Off	False Alarms 0.45	Correct Rejects 0.55

Measured Threshold



10%
Signal
Rate

		Response	
		Yes	No
Signal	On	Hits 0.52	Misses 0.48
	Off	False Alarms 0.14	Correct Rejects 0.86



d' computation with Excel

$$d' = \text{LOI.NORMALE.STANDARD.INVERSE}[p(H)] - \text{LOI.NORMALE.STANDARD.INVERSE}[p(FA)]$$

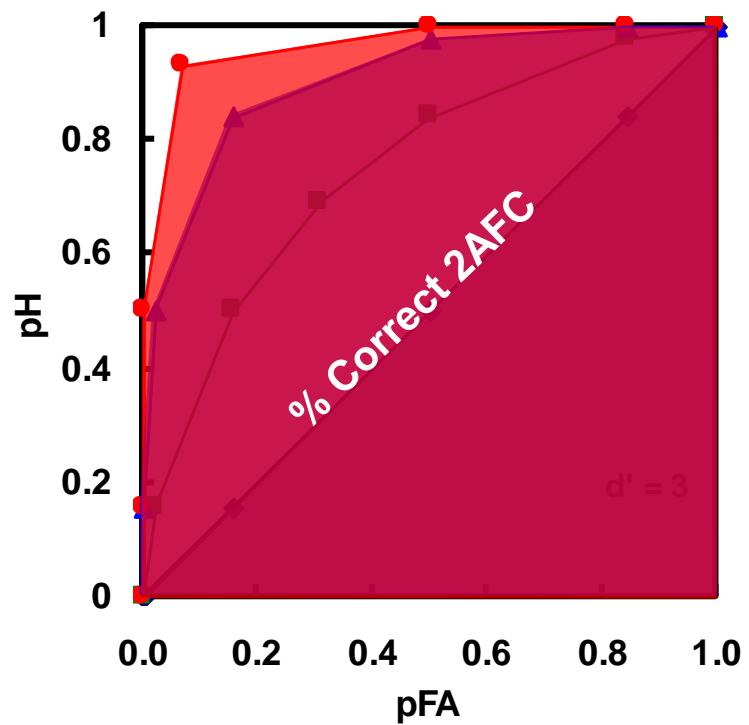
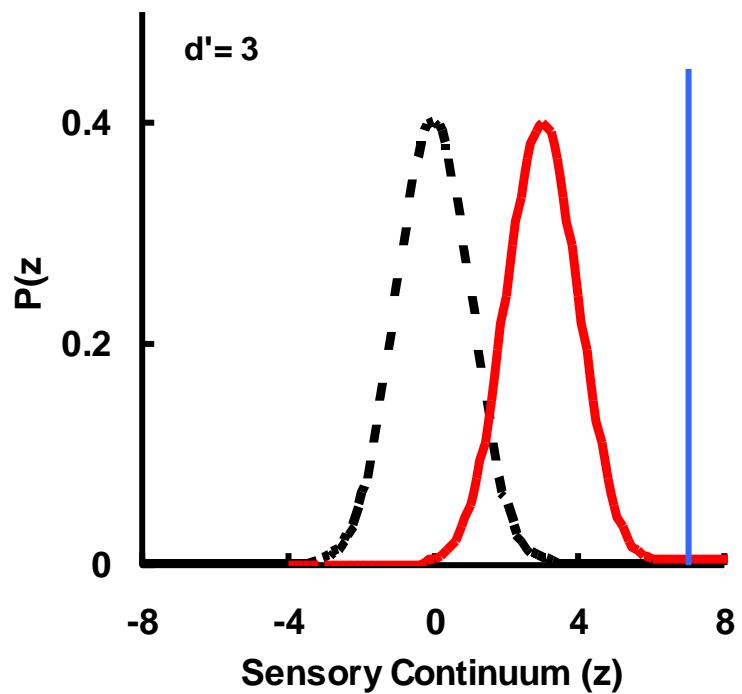
$$c_0 = -0.5 * \{\text{LOI.NORMALE.STANDARD.INVERSE}[p(H)] + \text{LOI.NORMALE.STANDARD.INVERSE}[p(FA)]\}$$

$$c_A = -\text{LOI.NORMALE.STANDARD.INVERSE}[p(FA)]$$

$$\beta = \text{LOI.NORMALE}(c_A; d'; 1; \text{FAUX}) / \text{LOI.NORMALE}(c_A; 0; 1; \text{FAUX})$$

	HITS	FA	HITS	FA	HITS	FA	HITS	FA
n	70	30	90	10	83	5	60	20
out of	100	100	100	100	100	100	100	100
N_Tot	200		200		200		200	
d'	1.0488		2.5631		2.5990		1.0950	
c0	0.0000		0.0000		0.3453		0.2941	
ca	0.5244		1.2816		1.6449		0.8416	
β	1.0000		1.0000		2.4536		1.3800	

Receiving Operating Characteristics (ROC)



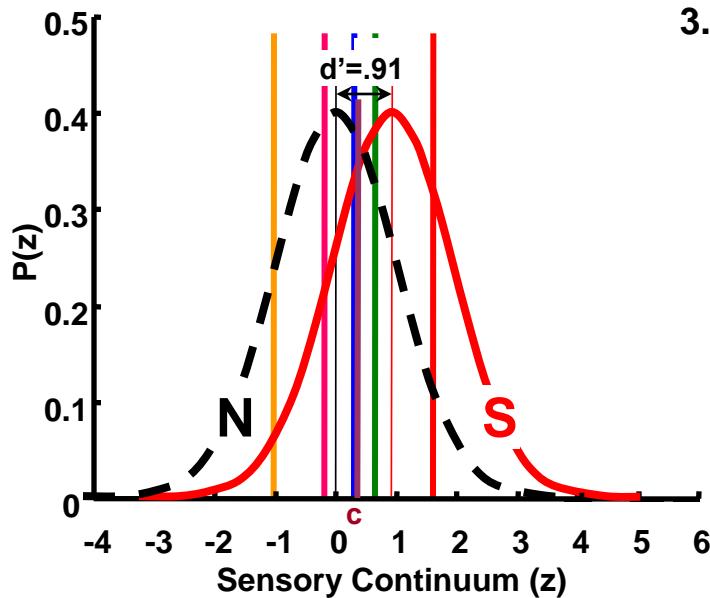
ROC & le Rating experiment

1. Faire le choix entre Oui et Non;

	Oui	Non	Tot.
S	218	157	375
N	90	285	375

2. Calculer le pH, pFA; puis d' & c.

pH	zH	pFA	zFA
$218/375 = .58$.202	$90/375 = .24$	$-.706$
d' zH-zFA	$.202 - (-.706) = .908$		
c $-.5(zH + zFA)$	$-.5(.202 - .706) = .252$		



2. Donner son niveau de certitude de 1 (peu sûr) à (par ex.) 3 (très sûr); l'on calcule les p pour chaque case en divisant sa fréq. par le no. total

	Oui				Non			
*	“3”	“2”	“1”		“1”	“2”	“3”	Tot.
S, H	.131	.251	.200		.160	.200	.059	1.00
N, FA	.021	.099	.120		.160	.301	.301	1.00

*Notez que l'échelle « Oui/Non » ci-dessus est équivalente à une échelle «Oui» avec 6 graduations, du plus sûr («6») au moins sûr («1»):

	Oui							
	“6”	“5”	“4”		“3”	“2”	“1”	Tot.

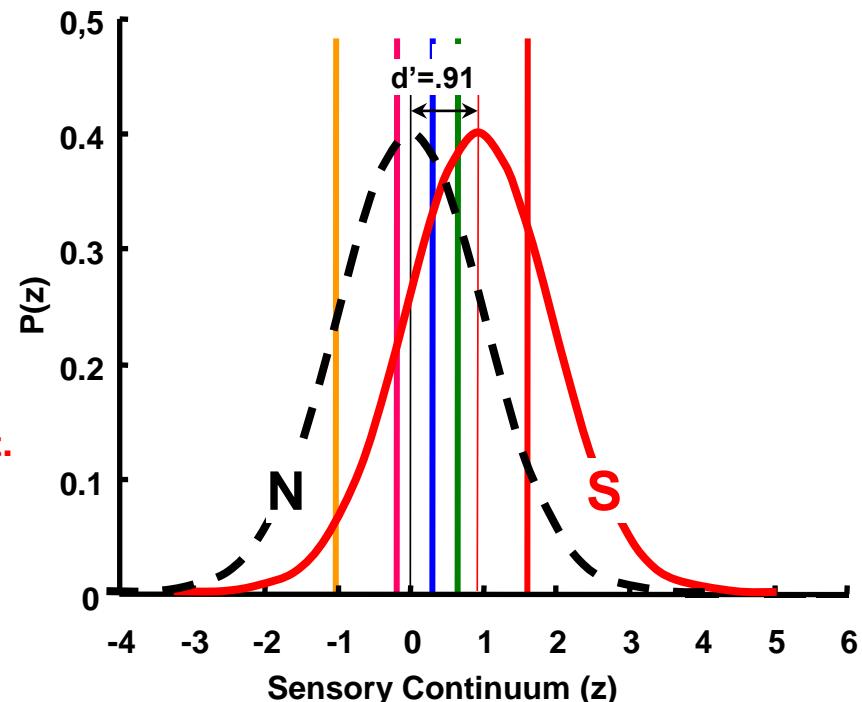
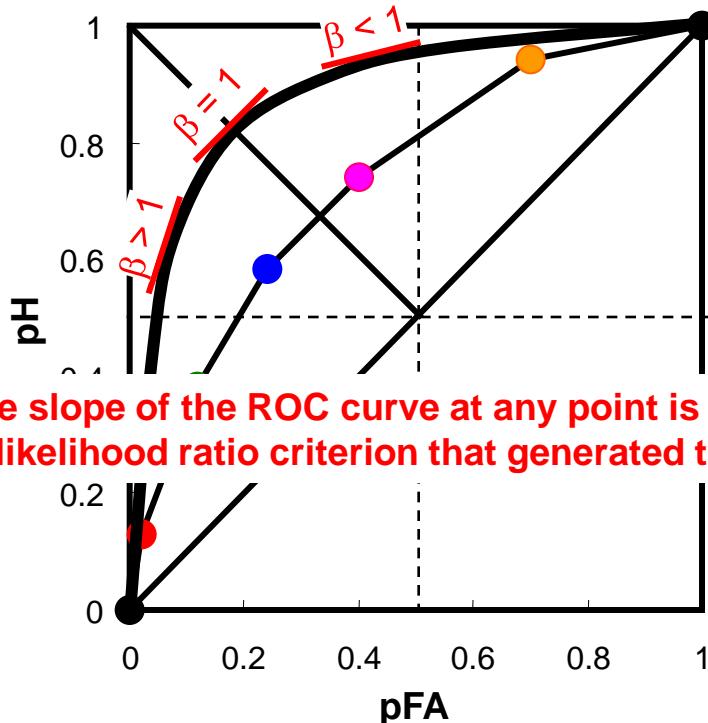
3. Pr chaque case, l'on calcule les **p cumulés de gauche à droite**, les scores z, les d' et c

	Oui							
	“6”	“5”	“4”		“3”	“2”	“1”	
H	.131	.382	.582		.742	.942	1.00	
FA	.021	.120	.240		.400	.701	1.00	
zH	-1.121	-0.301	0.207		0.649	1.573		
zFA	-2.037	-1.175	-0.706		-0.253	0.527		
d'	0.916	0.874	0.913		0.902	1.046		
c	1.579	0.738	0.250		-0.198	-1.050		

ROC & le Rating experiment

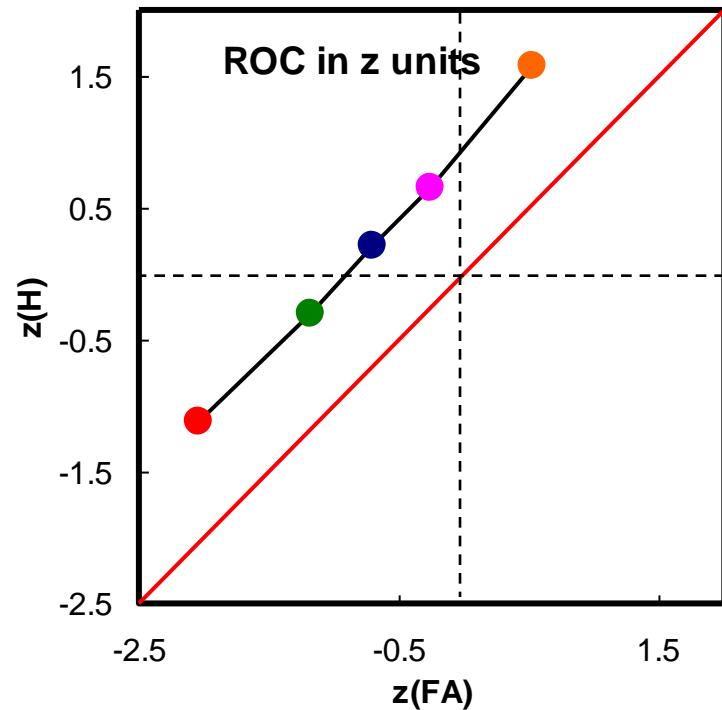
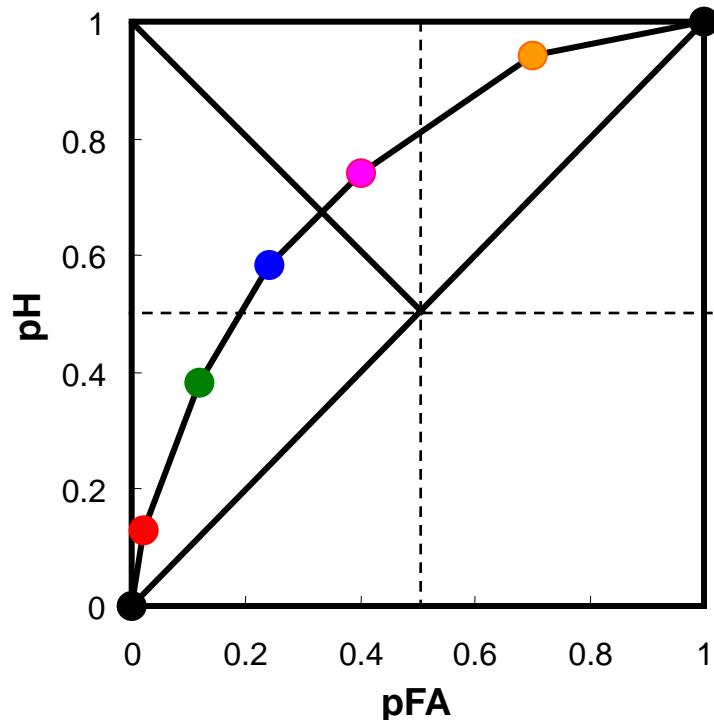
		OUI						NON					
		"3"		"2"		"1"		"1"		"2"		"3"	
		p	z	p	z	p	z	p	z	p	z	p	z
H		0.131	-1.122	0.382	-0.300	0.582	0.207	0.742	0.650	0.942	1.572	1.000	#####
FA		0.021	-2.034	0.120	-1.175	0.240	-0.706	0.400	-0.253	0.701	0.527	1.000	#####
d'		0.912		0.875		0.913		0.903		1.045		#NOMBRE!	
c_0		1.578		0.738		0.250		-0.196		-1.050		#NOMBRE!	

Note that a symmetrical ROC indicates that d' is independent of c_0

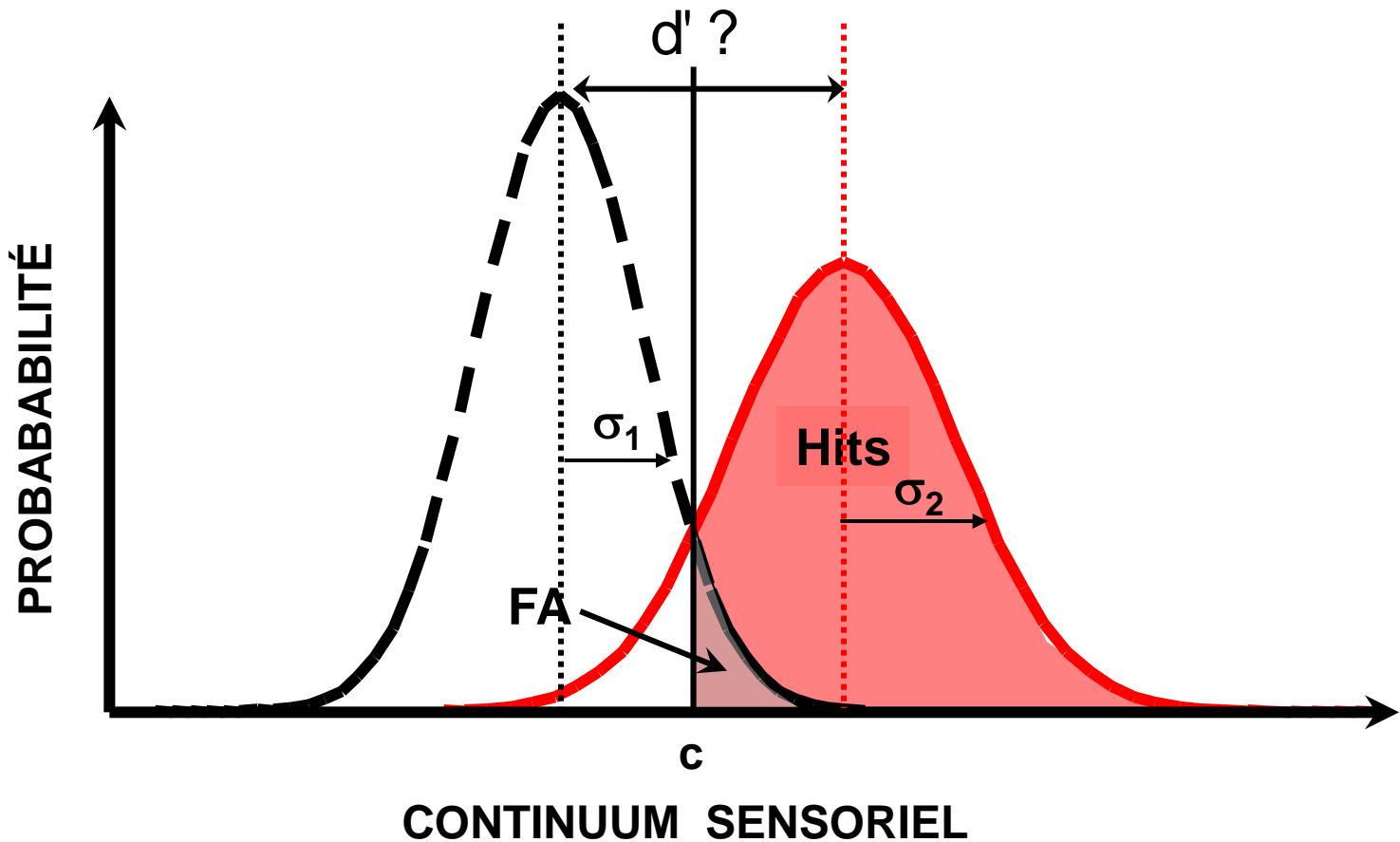


ROC & le Rating experiment

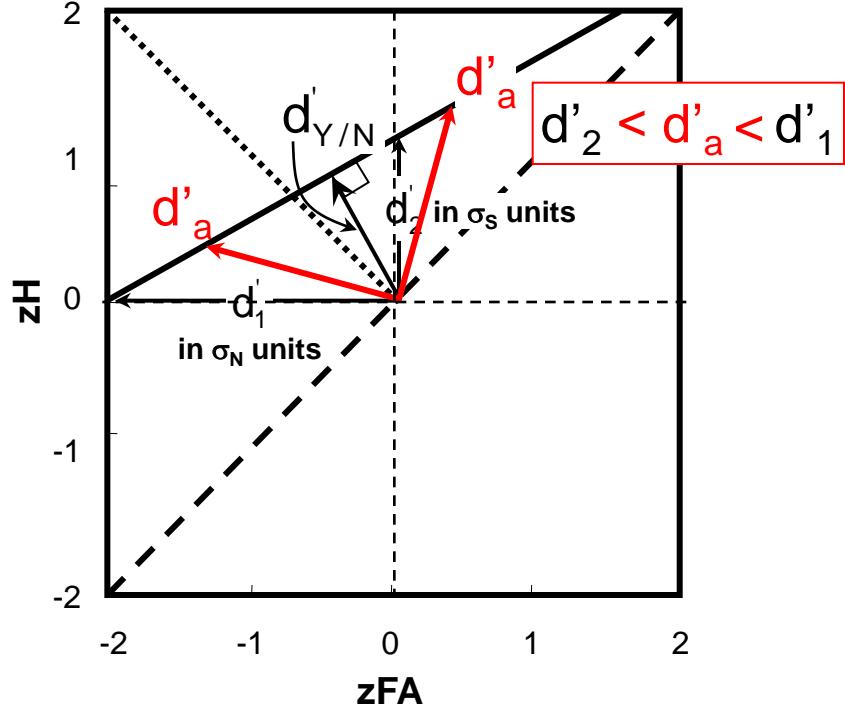
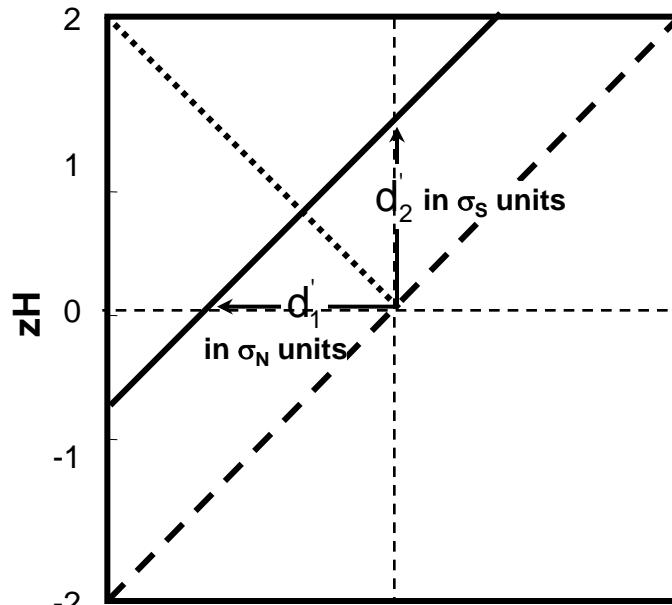
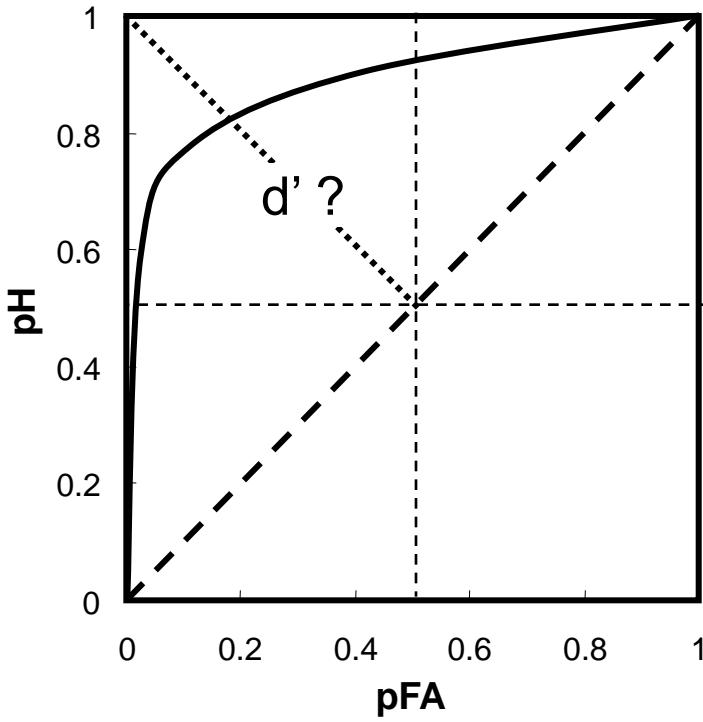
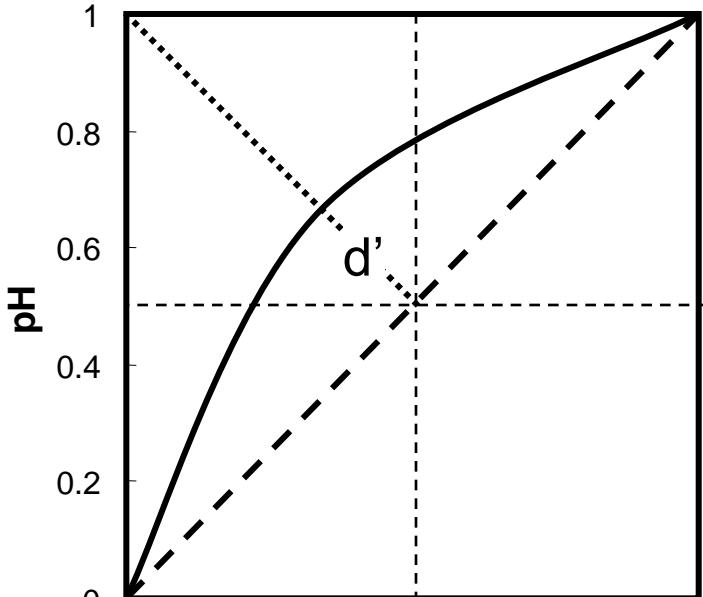
		OUI						NON					
		"3"		"2"		"1"		"1"		"2"		"3"	
		p	z	p	z	p	z	p	z	p	z	p	z
H		0.131	-1.122	0.382	-0.300	0.582	0.207	0.742	0.650	0.942	1.572	1.000	#####
FA		0.021	-2.034	0.120	-1.175	0.240	-0.706	0.400	-0.253	0.701	0.527	1.000	#####
d'		0.912		0.875		0.913		0.903		1.045		#NOMBRE!	
c0		1.578		0.738		0.250		-0.196		-1.050		#NOMBRE!	



d' with unequal variances

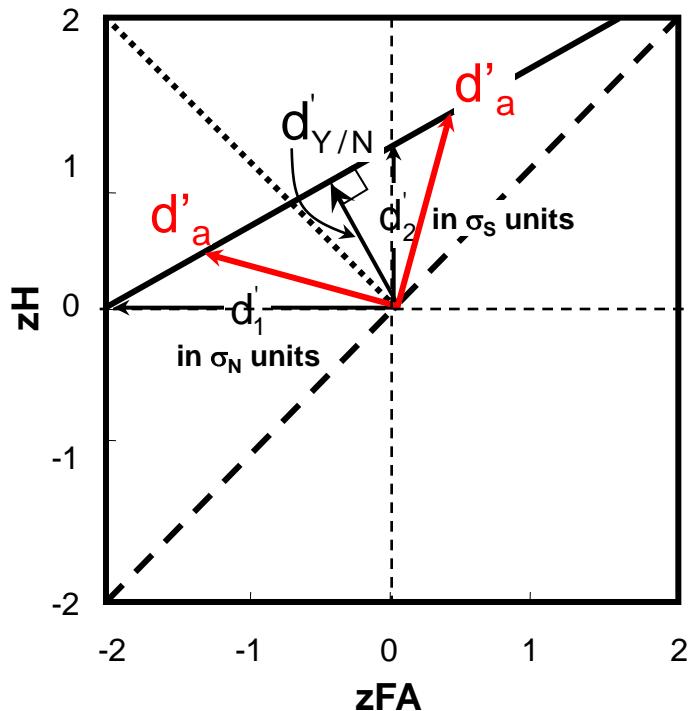


d' with unequal variances



$$d'_a = \sqrt{2}d'_{Y/N} = \Delta R / \sqrt{\sigma_1^2 + \sigma_2^2}$$

d' with unequal variances



The index d_a has the properties we want.

1. It is intermediate in size between d'_1 and d'_2 .
2. It is equivalent to d' when the ROC slope is 1, for then the perpendicular line of length $D_{Y/N}$ coincides with the minor diagonal, and the two lines of length d_a coincide with the d'_1 , and d'_2 segments.
3. It turns out to be equivalent to the difference between the means in units of the *root-mean-square* (*rms*) standard deviation, a kind of average equal to the square root of the mean of the squares of the standard deviations of S1 and S2.

To find d_a from an ROC that is linear in z coordinates, it is easiest to first estimate d'_1 , d'_2 and the slope $s = d'_1/d'_2$. Because the standard deviation of the S1 distribution is s times as large as that of S2, we can set the standard deviation of S1 to s and that of S2 to 1.

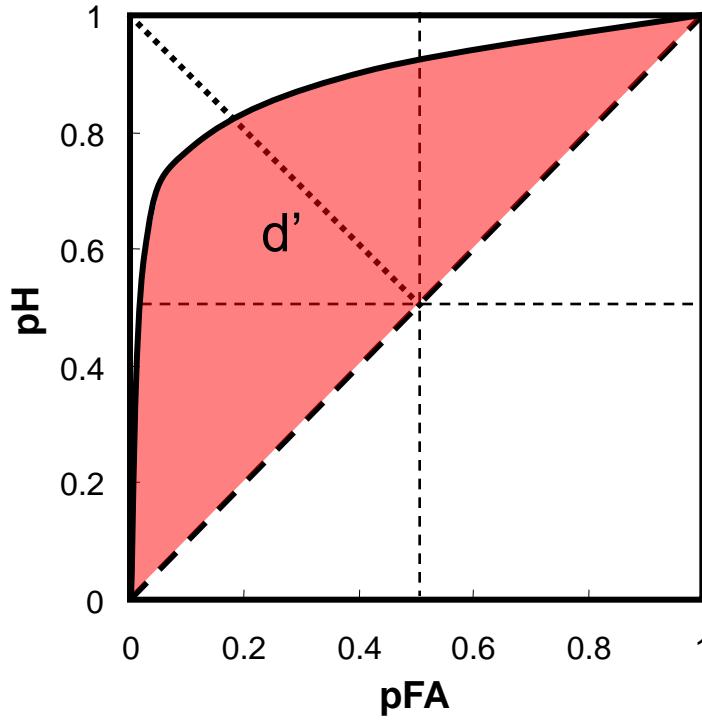
To find d_a directly from one point on the ROC once s is known:

$$d'_a = \frac{d'_2}{[.5(1+s^2)]^{.5}} = d'_2 \left(\frac{2}{1+s^2} \right)^{.5}$$

$$d'_a = [z(H) - sz(F)] \left(\frac{2}{1+s^2} \right)^{.5}$$

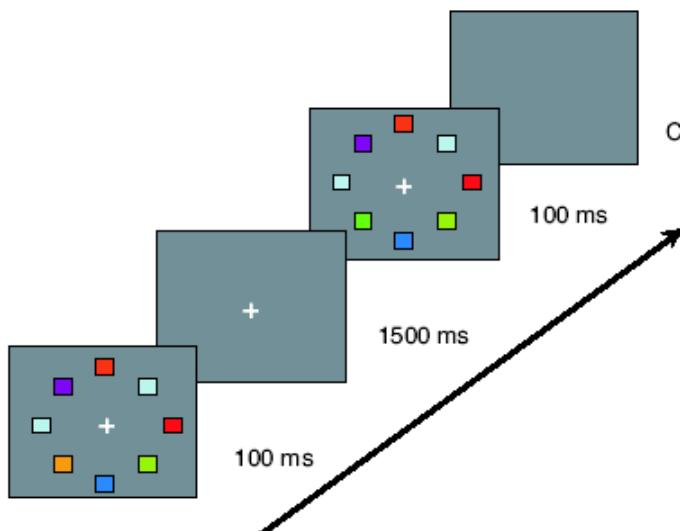
d' with unequal variances

$$\text{Area under ROC, } Az = \Phi(D_{YN}) = \Phi\left(\frac{d_a}{\sqrt{2}}\right)$$



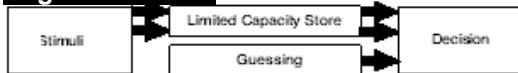
Sometimes a measure of performance expressed as a *proportion* is preferred to one expressed as a distance. The index Az , is such a proportion and is simply D_{YN} transformed by the cumulative normal distribution function Φ , i.e. $\Phi(D_{YN})$:

Az is the area under the normal-model ROC curve, which *increases from .5 at zero sensitivity to 1.0 for perfect performance*. It is basically equal to %Correct in a 2AFC experiment. **It is a truly nonparametric index of sensitivity.**

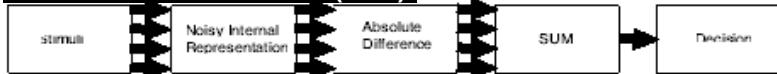


Schematic of a single trial used for the set size and the target number experiments. In the orientation and spatial frequency experiments, the colored squares were replaced with Gabor patches.

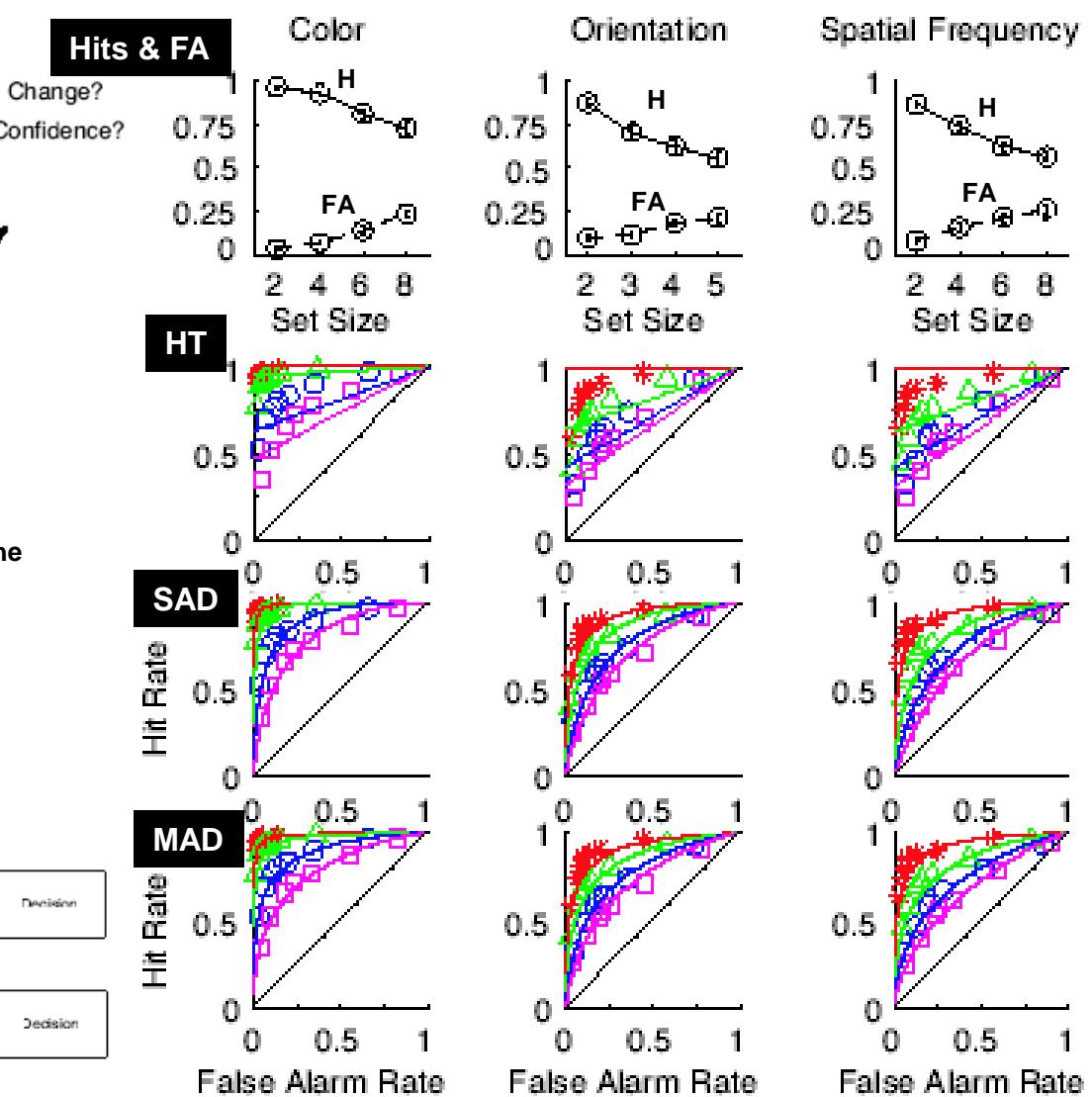
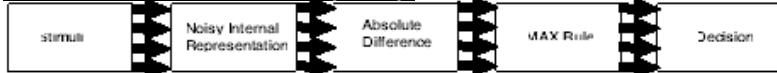
High-Threshold



Sum Absolute Difference (SAD)

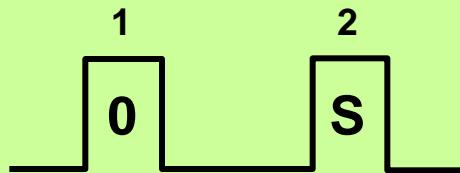


Max Absolute Difference (MAD)



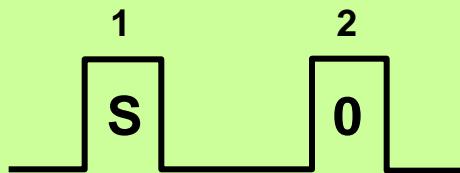
ROCs obtenus avec une méthode de « rating » sur une échelle de 1 à 4. Different symbols represent performance at different set sizes: set-size 2 for color, orientation and SF – red stars; set-size 4 for color and SF, set-size 3 for orientation – green triangles; set-size 6 for color and SF, set-size 4 for orientation – blue circles; set-size 8 for color and SF, set-size 5 for orientation – purple squares.

LA RELATION ENTRE Y/N & 2AFC



$$A = \text{« 1 »} - \text{« 2 »} \Rightarrow -S$$

$$\Rightarrow |A - B| = 2S$$

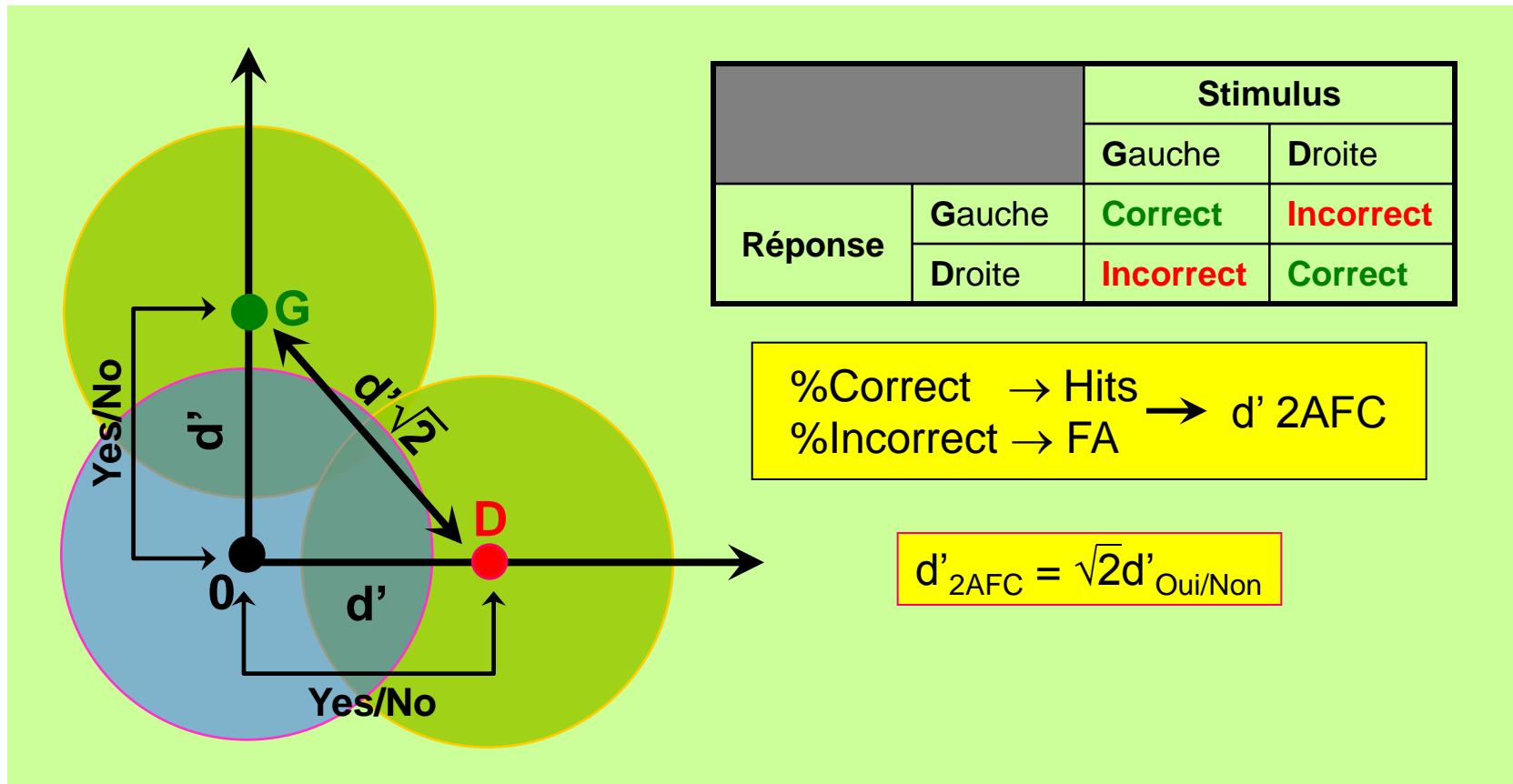


$$B = \text{« 1 »} - \text{« 2 »} \Rightarrow S$$

$$\Rightarrow SD = \sqrt{2\sigma} = \sigma\sqrt{2}$$

$$\Rightarrow d'_{2AFC} = \frac{2S}{\sigma\sqrt{2}} = \frac{S\sqrt{2}}{\sigma} \Rightarrow \sqrt{2}d'_{Y/N}$$

LA RELATION ENTRE Y/N & 2AFC

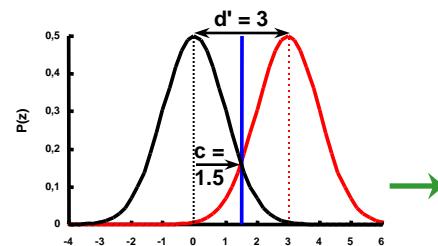


See MacMillan & Creelman (2005, 2nd ed.) pp 166-170.

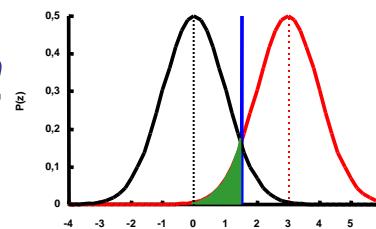
Reasons for “invisibility”

So, objects may be “invisible” for only 2 + 1 reasons;
because the internal activity they yield upon presentation:

- is undistinguishable from noise (null *sensitivity*)
→ $d' = 0$,

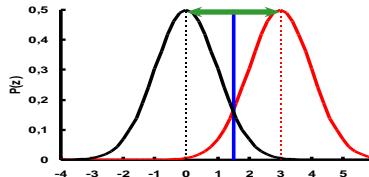


- is below Sj's criterion
→ the object is *ignored*, or



- because Sj's report on the presence/absence of the stimulus is solicited within a time delay beyond his/her mnemonic capacity (the case of *change blindness*). •

SENSITIVITY [♣]



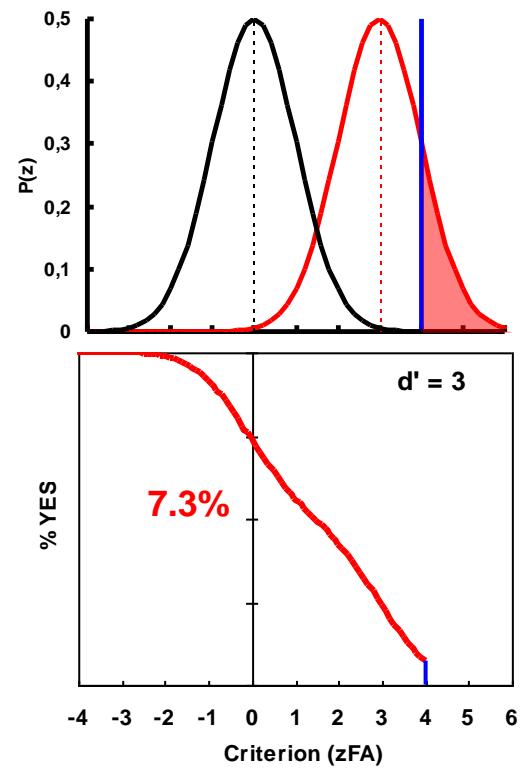
Failure of discriminating Signal from Noise has a triple edge:

- Stimuli may be *out of the standard window of visibility* [♣] (Signal \leq Internal noise)
 - ⇒ e.g. ultraviolet light, SF > 40 c/deg, TF > 50 Hz
 - ⇒ reduced window of visibility (experimental or pathological – e.g. blindsight)
- Stimuli may be "*masked*" by *external noise* [♣] so that the S/N ratio is decreased by means of:
 - ⇒ increasing N (external noise impinges on the detecting mechanism → the classical *pedestal effect*, or increases spatial/temporal *uncertainty* → e.g. the "*mud-splash effect*")
 - ⇒ decreasing S (external noise activates an inhibitory mechanism → *lateral masking/metacontrast*) [♣]
- Change of the *transducer* [♣] (experimentally or neurologically induced *gain-control* effects, *normalization failure* ...) ↓

CRITERION

The response criterion can be assimilated to response bias (and everything that goes with it, i.e. predisposition, context effects, etc.)

- can be manipulated in a number of ways:
 - ⇒ probability
 - ⇒ pay-off
- can be affected by experience in general
- and, possibly, by some neurological conditions
 - ⇒ blindsight
 - ⇒ neglect / extinction
 - ⇒ attentional deficit syndromes



AN EXAMPLE: CHANGE BLINDNESS

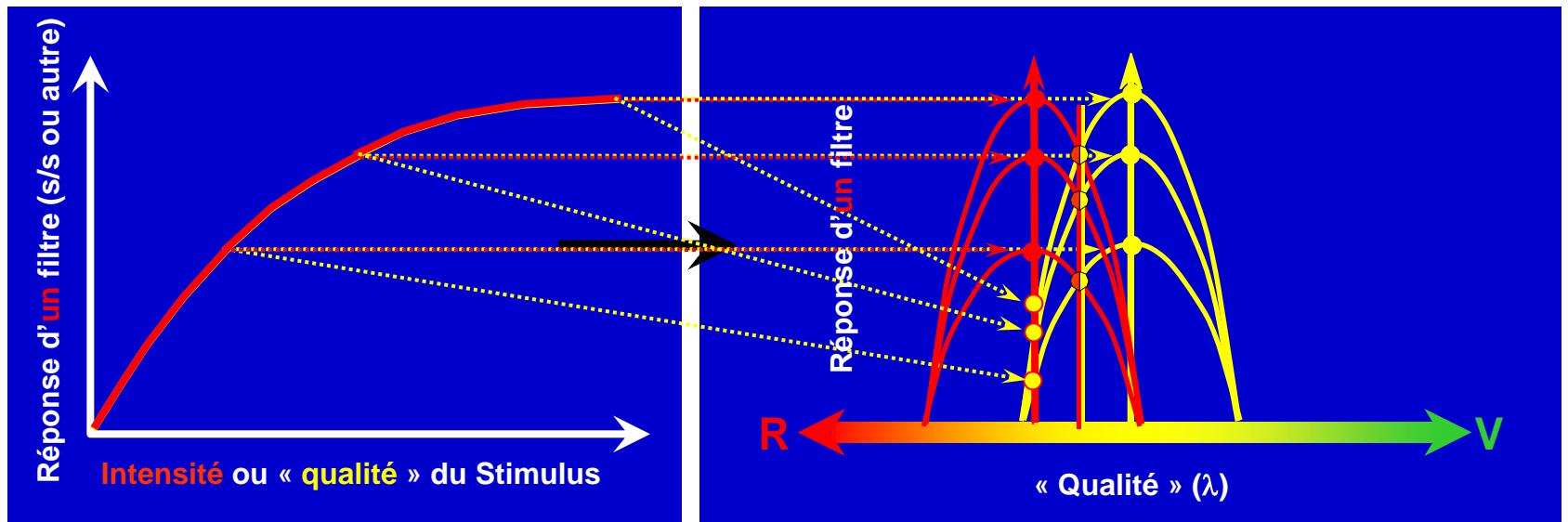
Dinner

Money

Airplane

CANAUX, BRUIT
et
THÉORIE DE LA DÉTECTION DU SIGNAL

Le principe de l'UNIVARIANCE



$$R = R_{\max} \frac{I^n}{\sigma^n + I^n} + R_s$$

I = stimulus intensity

R = response

R_{\max} = max resp.

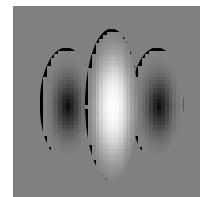
N = max slope

S = semi-saturation cst.

R_s = spontaneous R

Un autre

Un Canal,
Filtre.
Chp Récep.



RESPONSE NORMALIZATION

Normalization works (here) by
dividing each output
by the sum of all outputs.

Divisive normalization

Consider a collection of linear operators and energy mechanisms, with various receptive-field centers (covering the visual field) and with various spatiotemporal frequency tunings. Let $E_i(t)$ be the outputs of each of the energy mechanisms. Normalization, in the model, works by dividing each output by the sum of all of the outputs:

$$\bar{E}_i(t) = \frac{E_i(t)}{\sigma^2 + \sum_i E_i(t)}, \quad (4)$$

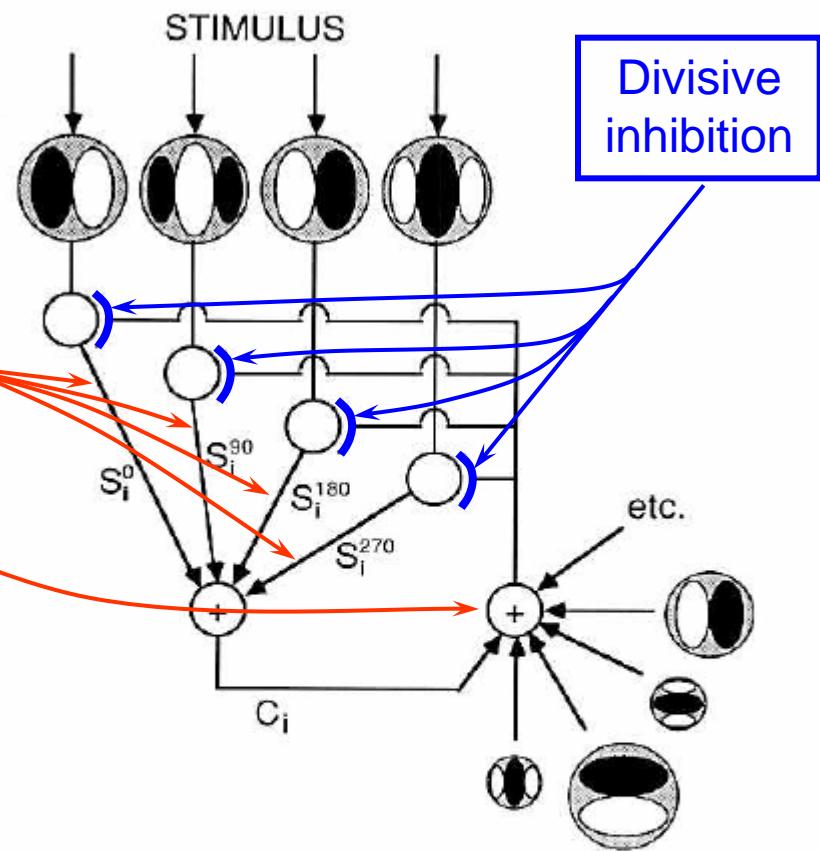
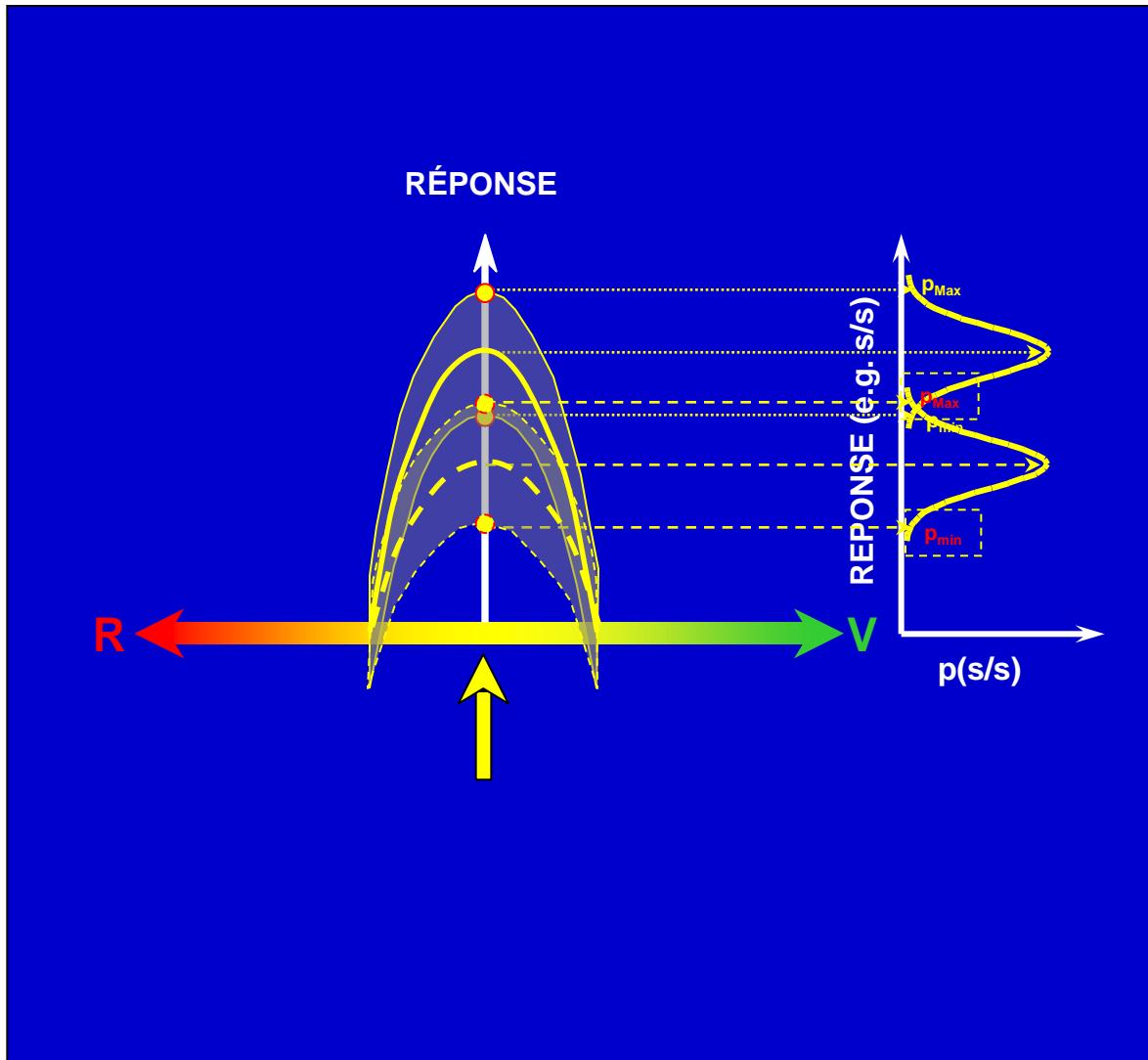


Fig. 1. Diagram of the various stages of the model. Linear weighting functions are depicted as circles, subdivided into excitatory (bright) and inhibitory (dark) subregions. The S_i^0 labels represent simple cell outputs, and the C_i label represents a complex cell output. The feedback signal is the combined energy at all orientations and nearby spatial frequencies, averaged over space and time. The feedback signal suppresses the simple cell responses by way of divisive suppression.

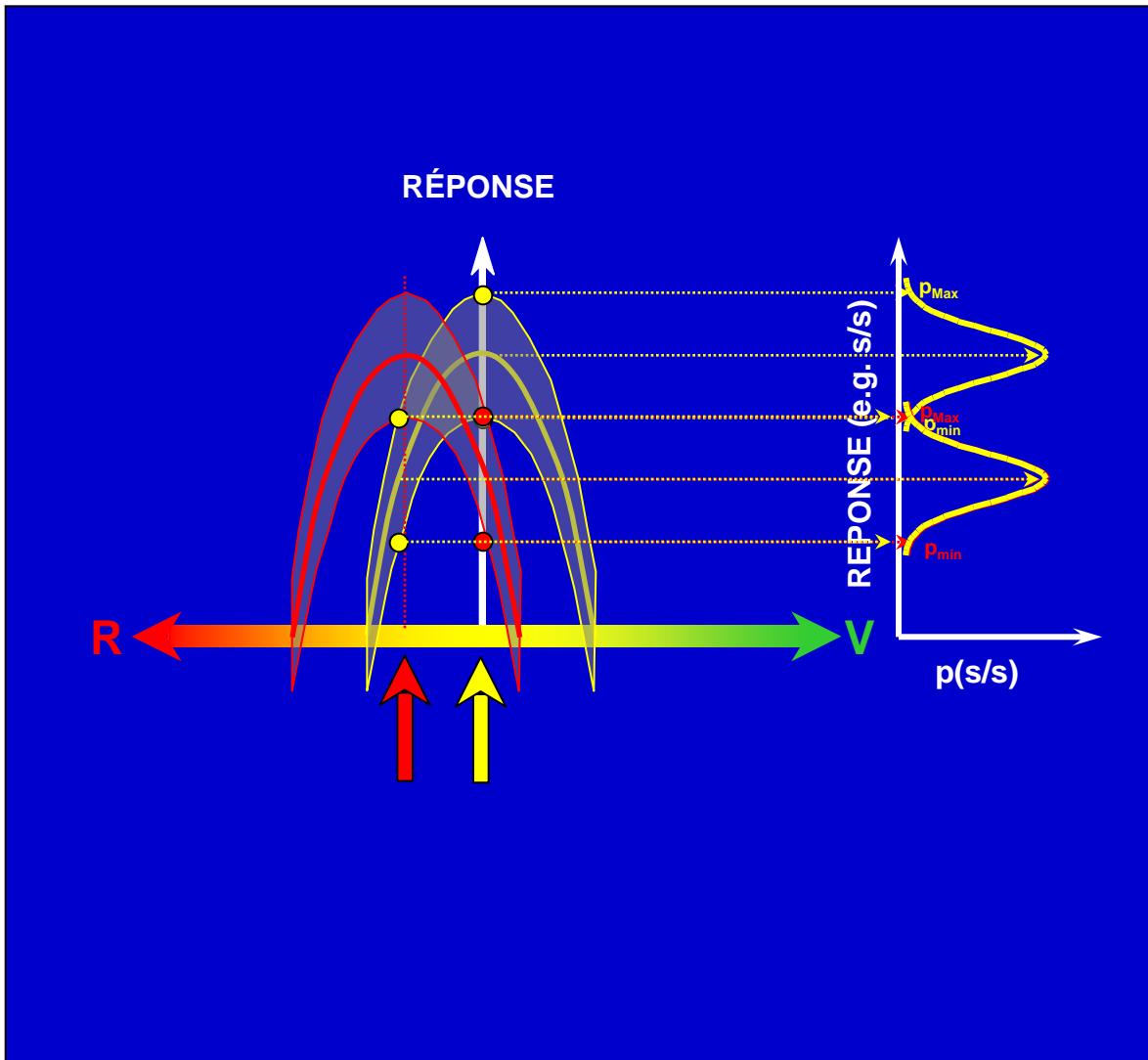
CANAUX & PROBABILITÉ DE RÉPONSE

Intensity Discrimination



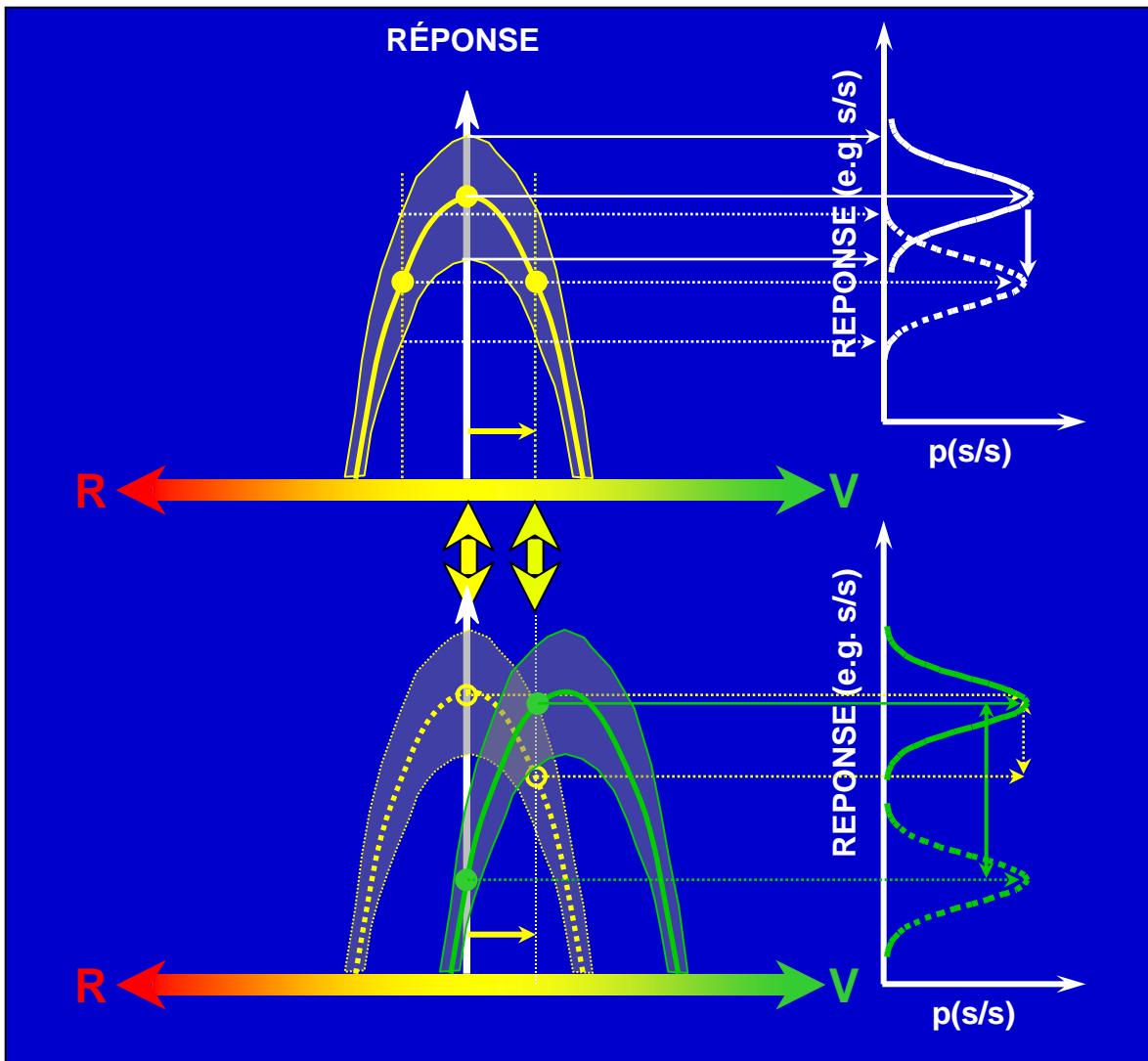
CANAUX & PROBABILITÉ DE RÉPONSE

Within & Across Channels Discrimination



CANAUX & PROBABILITÉ DE RÉPONSE

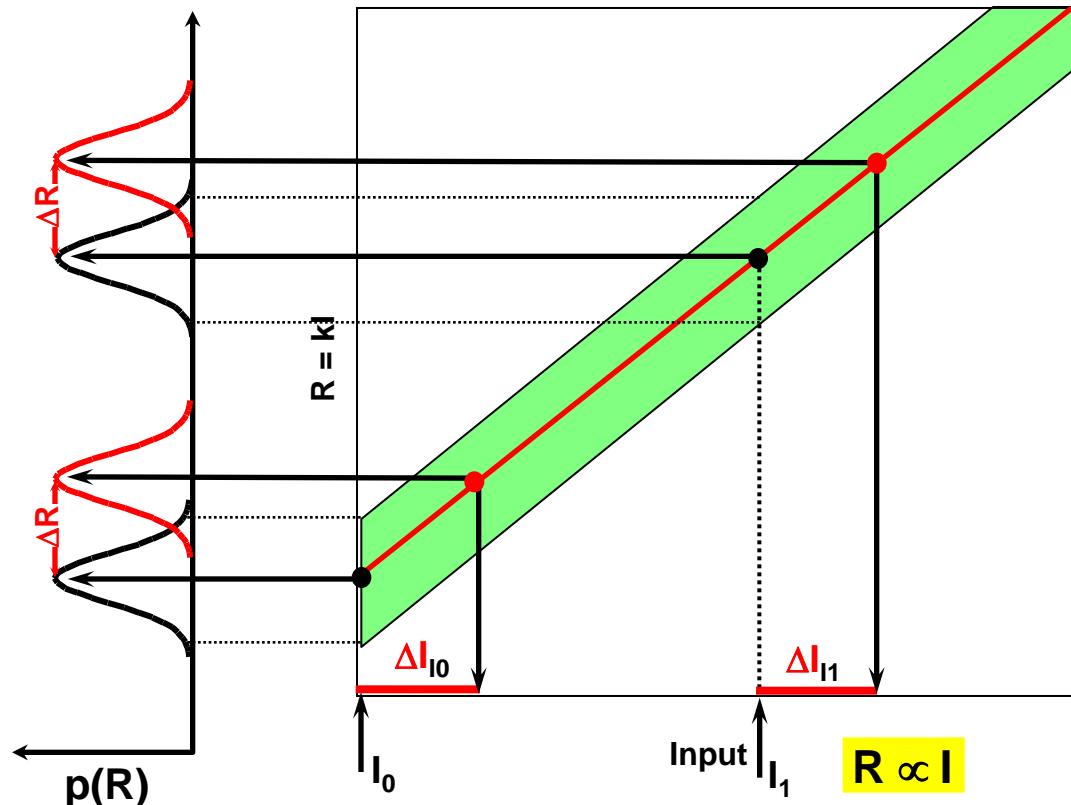
« OFF-LOOKING » CHANNEL



TRANSDUCTION

$$R = kI$$

$$\sigma = \text{cst.}$$

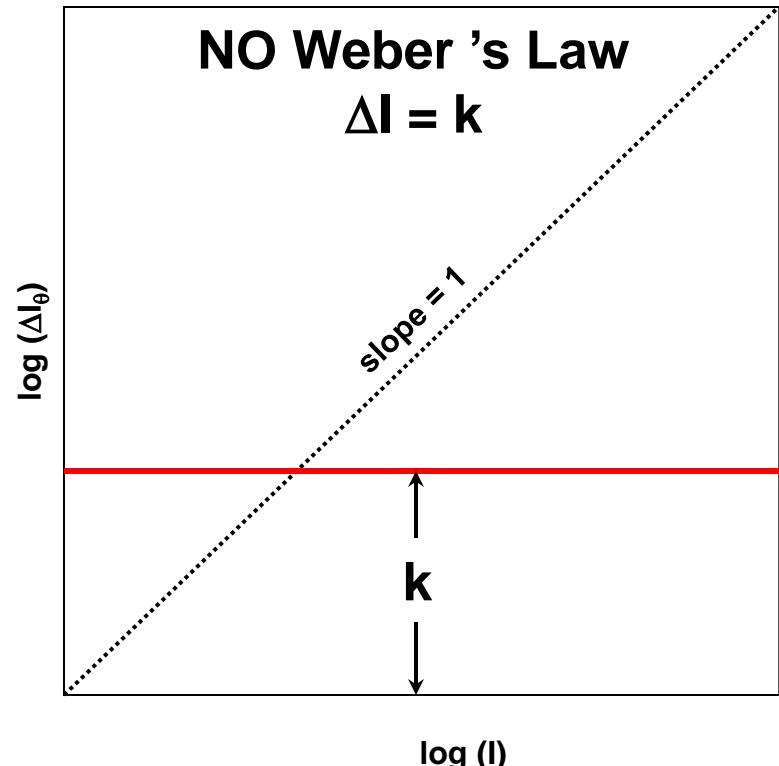


$$\Delta R \propto \Delta I$$

$$\Delta R_\theta = k \text{ (at } \theta; \text{ iff } \sigma = \text{cst.})$$

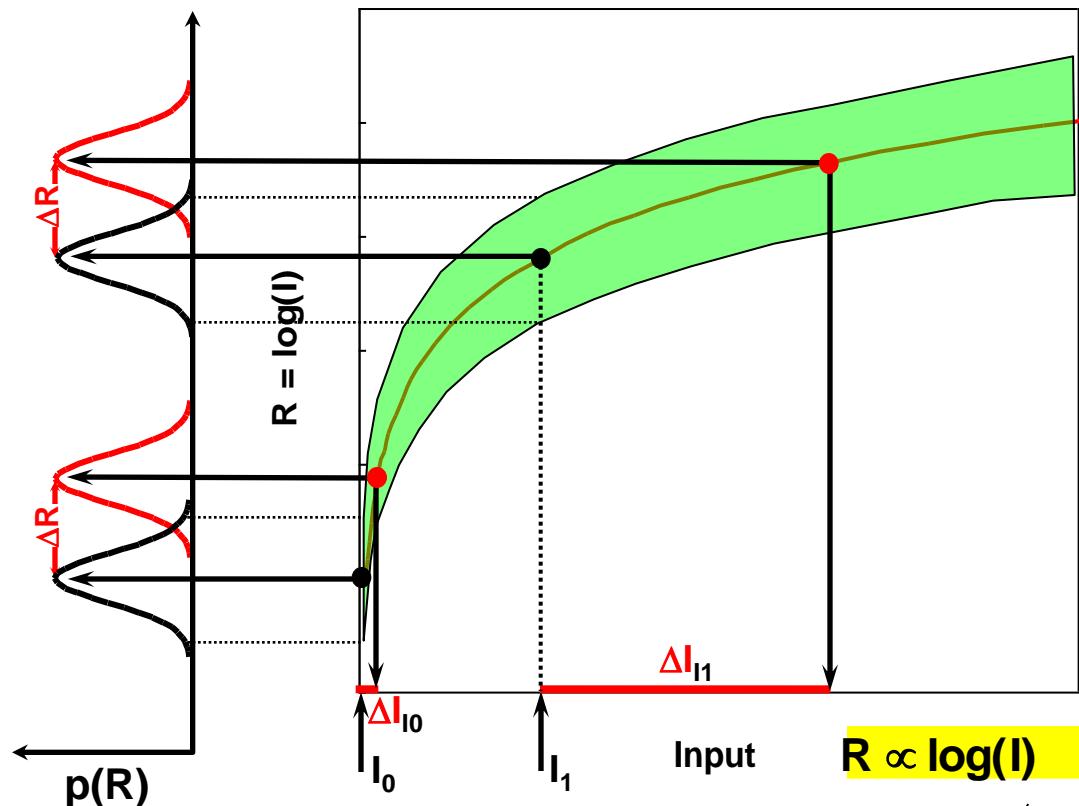
$$\Delta I_\theta = k$$

NO Weber's Law
 $\Delta I = k$

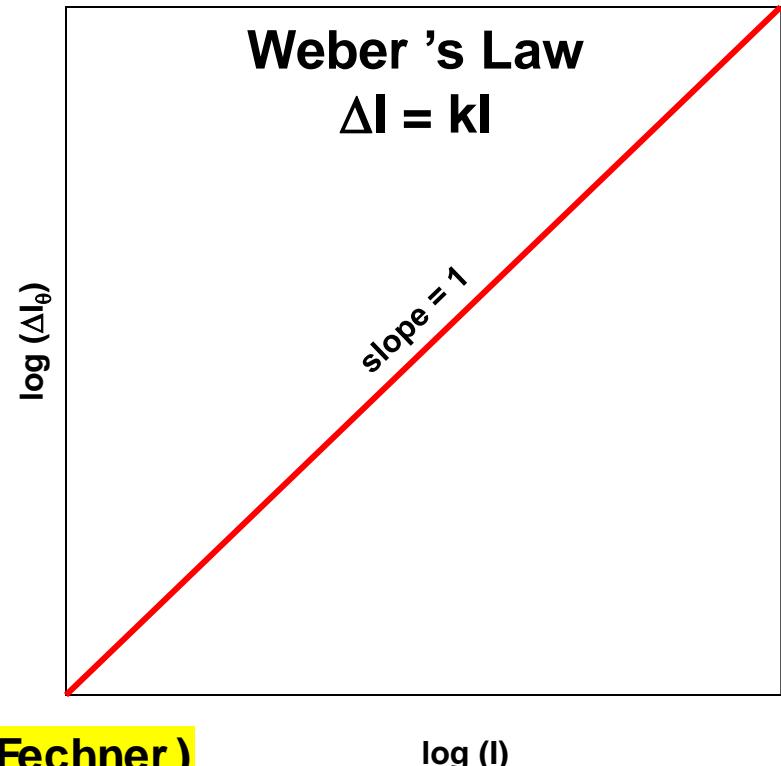


TRANSDUCTION

$R \propto \log(I)$ (Fechner)
 $\sigma = \text{cst.}$



Weber's Law
 $\Delta I = kI$



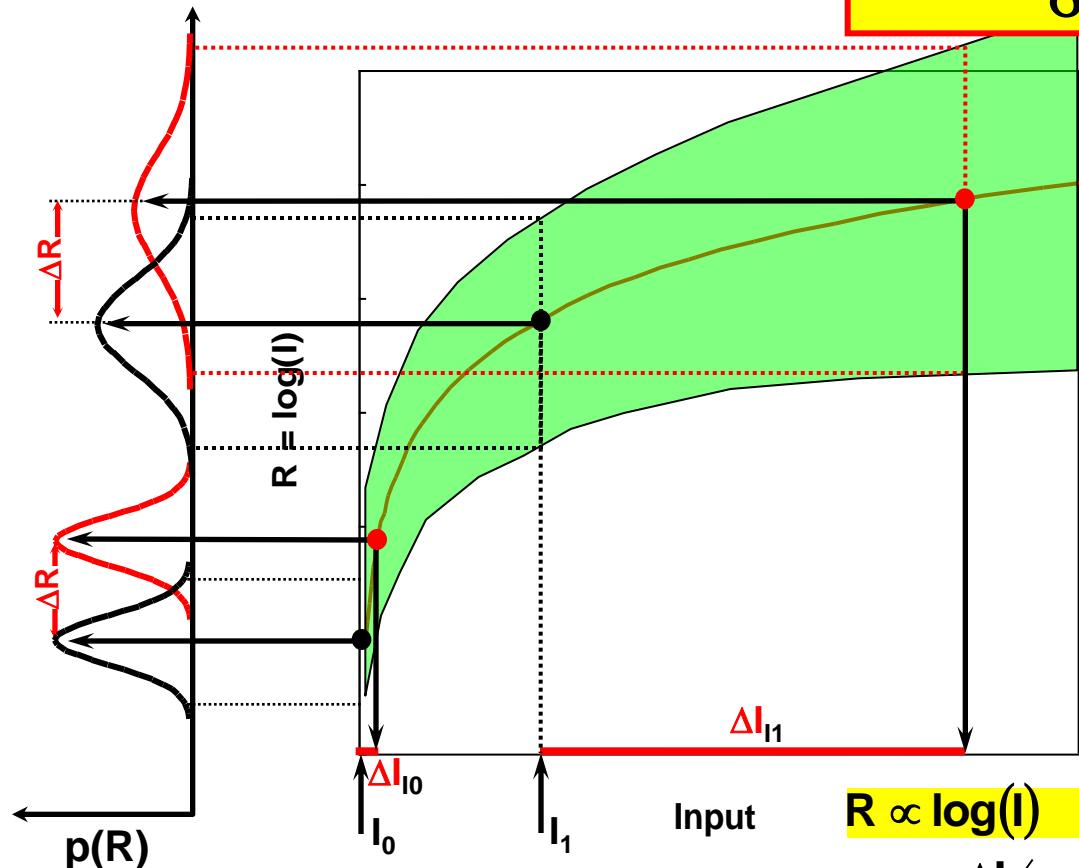
$R \propto \log(I)$ (Fechner)
 $\Delta R \propto \frac{\Delta I}{I}$

$\Delta R_\theta = k$ (at θ ; iff $\sigma = \text{cst.}$)

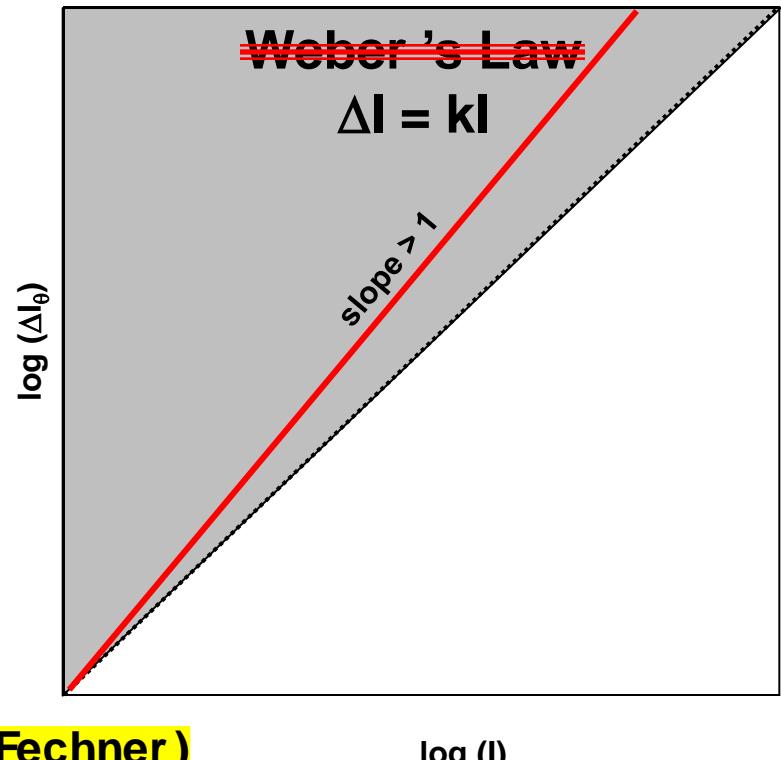
$\Delta I_\theta = k'I$ (Weber's Law)

TRANSDUCTION

$R \propto \log(I)$ (Fechner)
 $\sigma \propto R$



Weber's Law
 $\Delta I = kI$



$R \propto \log(I)$ (Fechner)
 $\Delta R \propto \frac{\Delta I}{I}$

$\Delta R_\theta \propto R^\beta$ (at θ ; $\sigma \propto R^\beta$)

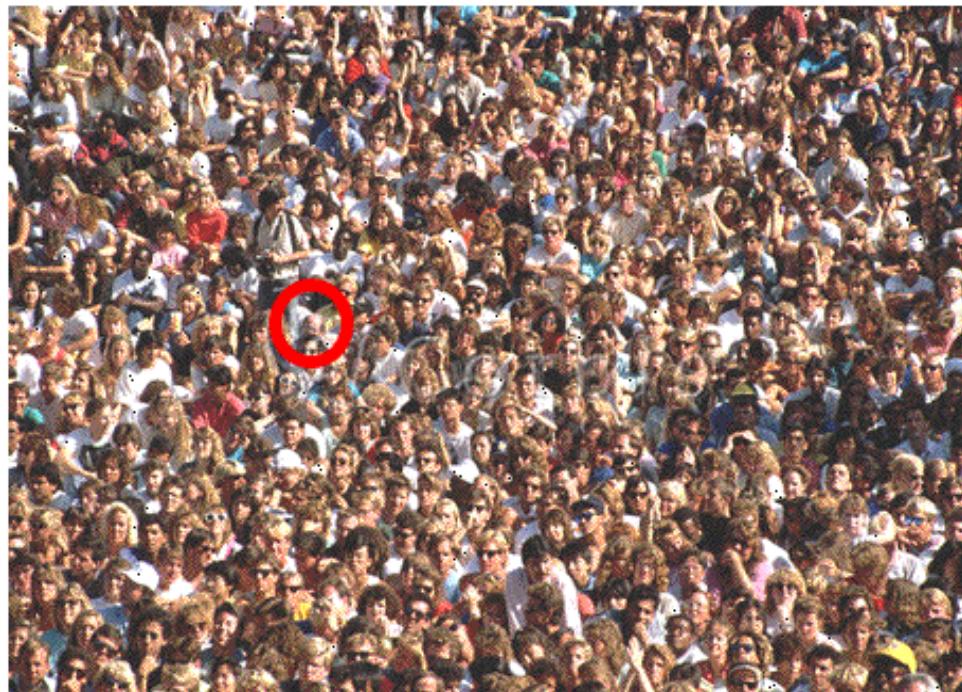
$\Delta I_\theta = kI(\log I)^\beta$ (Weber's Law iff $\beta = 0$)

**VISUAL SEARCH
and
SIGNAL DETECTION THEORY**

Your friends with the green scarves at
Pamplona jump out at you

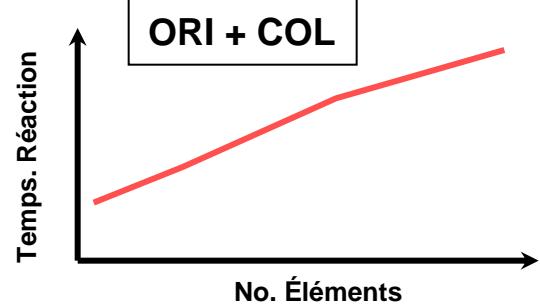
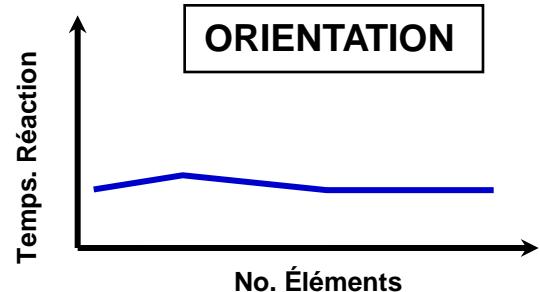
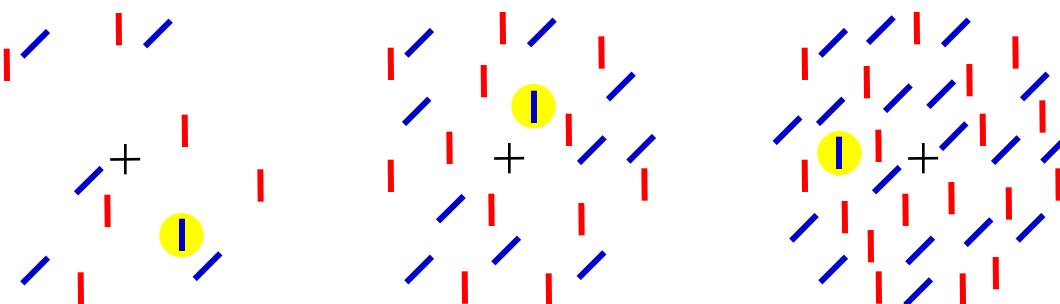
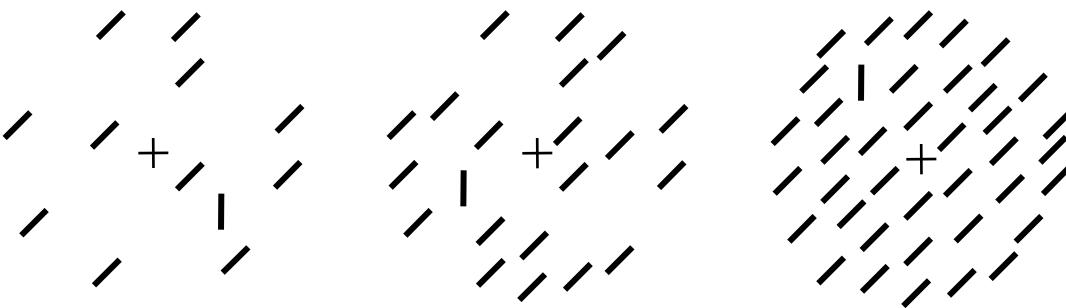


But finding a bald man at a
rock concert is hard



Treisman A.M. & Gelade G. (1980)

Le paradigme type



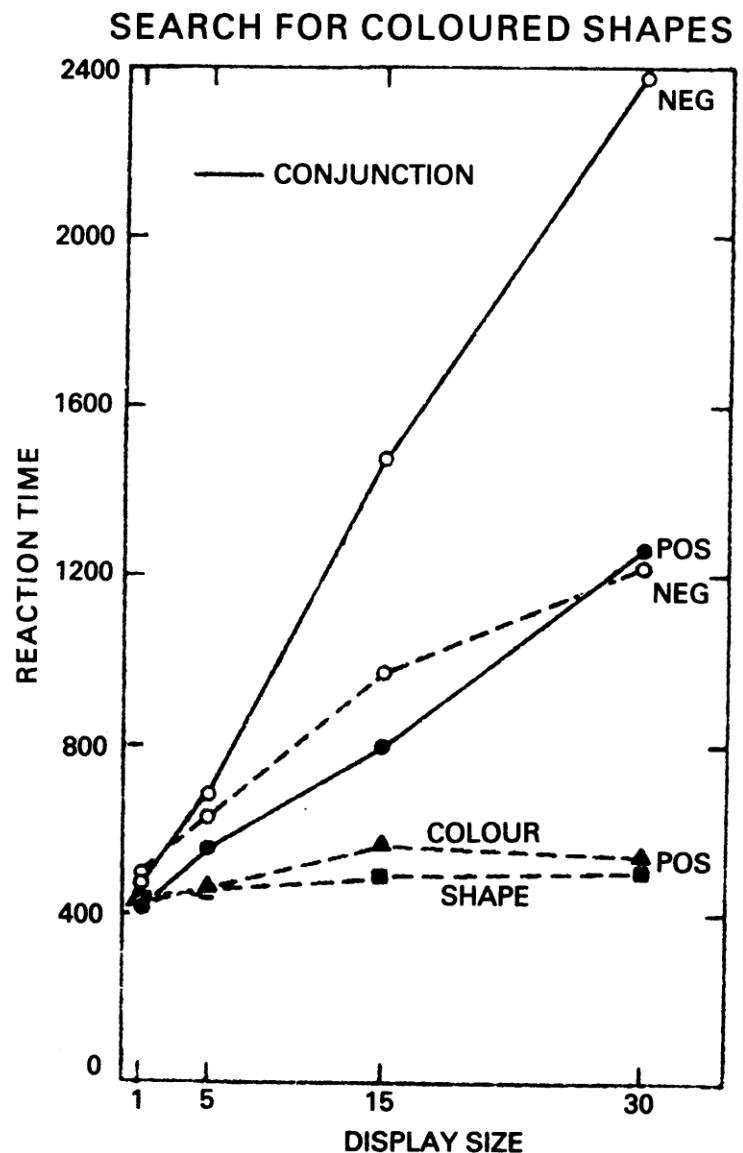
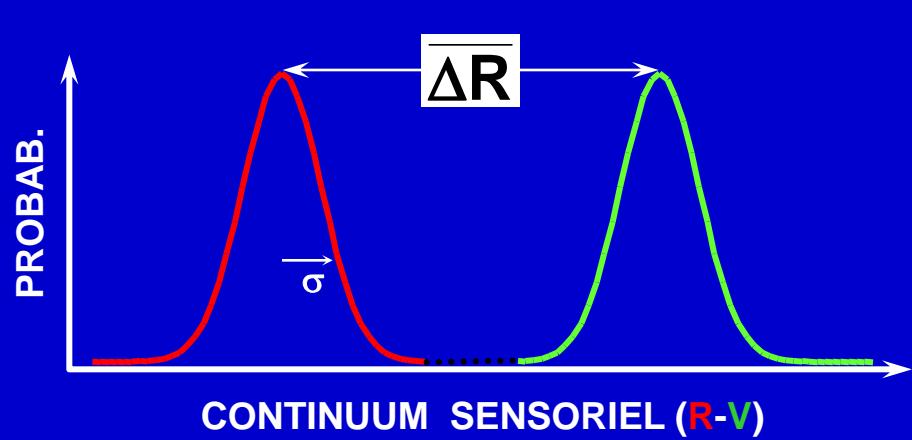
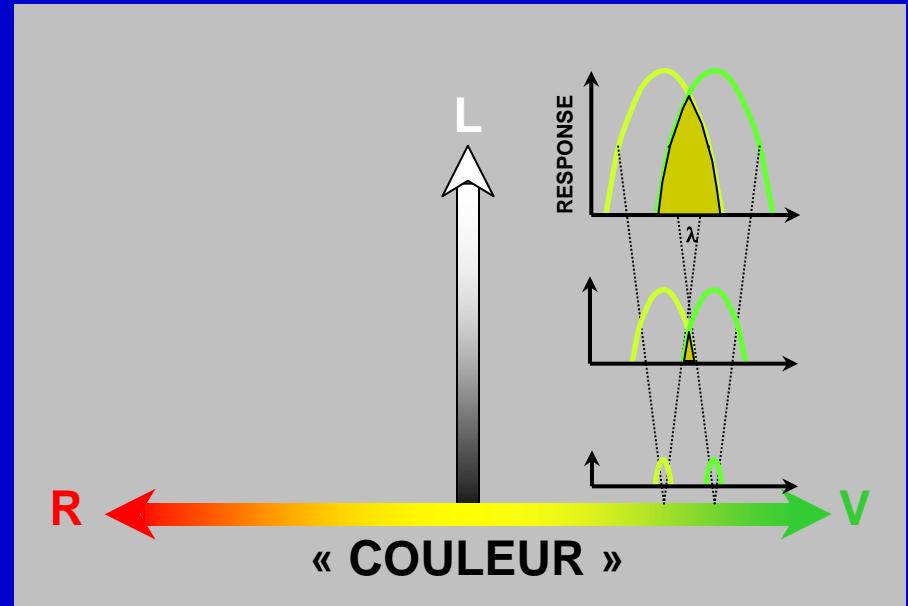
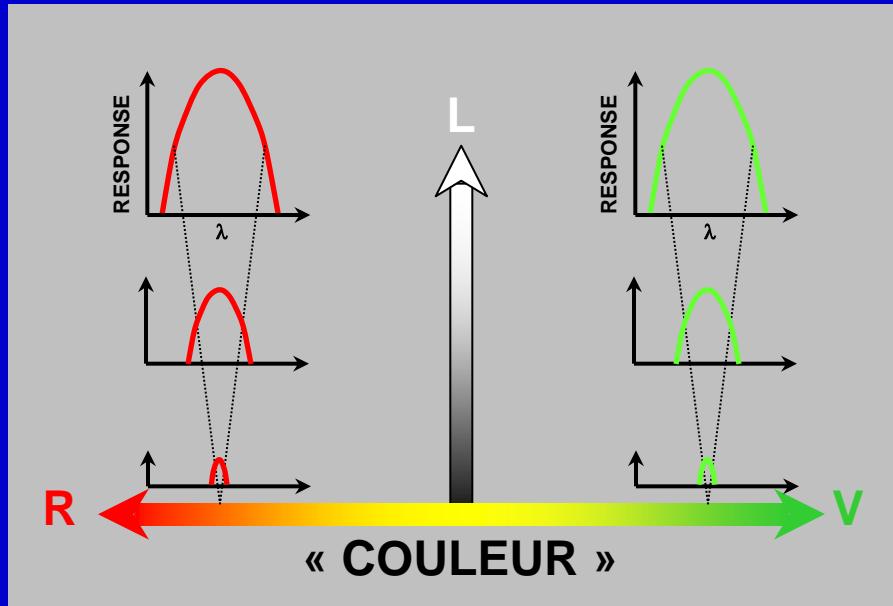
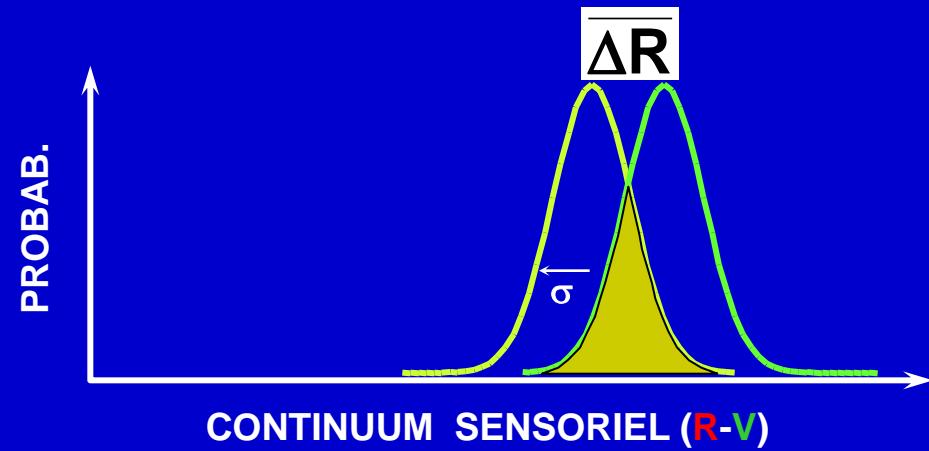


FIG. 5.19. Search for conjunctions and single-feature targets defined by colour and shape.
(Reproduced from Treisman & Gelade, 1980, with permission.)

LE MODÉLE STANDARD : LA THÉORIE DE LA DÉTECTION DU SIGNAL



d' n'est pas mesurable



$$d' = \frac{\overline{\Delta R}}{\sigma}$$

