Psychometric functions

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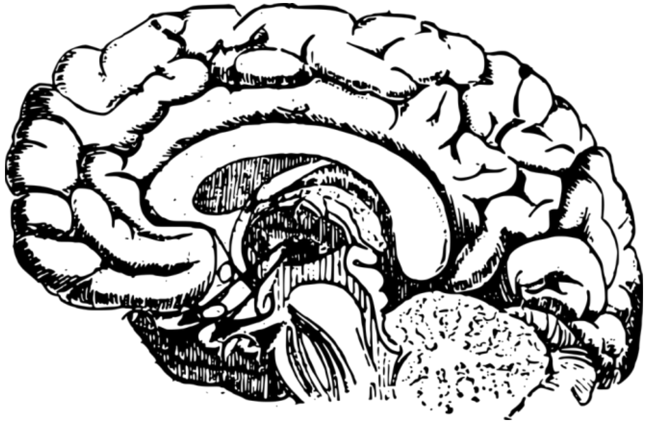
Objective vs subjective

- Objective – reality in the world
- Subjective – interpretation of our brain

?



Some basic

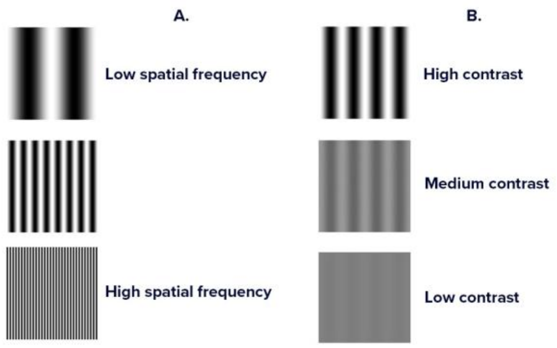
- Luminance and contrast
- Detection vs discrimination

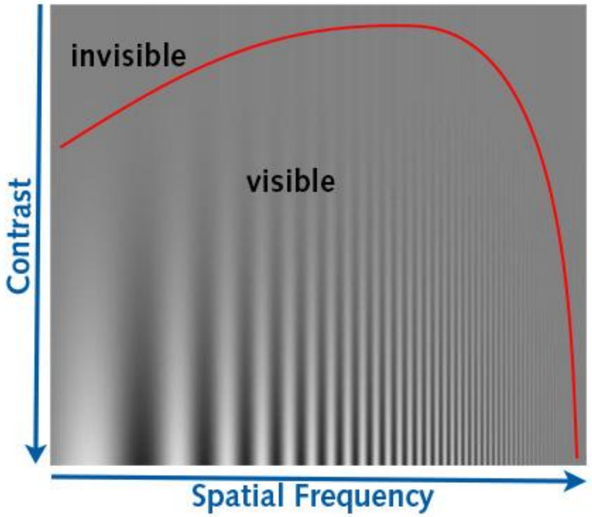
Luminance - I

- Luminance is the physical measure of light intensity emitted or reflected from a surface
- It is typically measured in candela per square meter (cd/m^2).
- Psychophysics studies how physical stimuli relate to perception. In vision this means the relationship between:
  - Physical luminance (stimulus)
  - Perceived brightness (sensation)

Contrast

- Contrast = relative difference in luminance between a stimulus and its background
- We are sensitive to changes in luminance, not absolute luminance levels!
- Contrast sensitivity is dependent on spatial frequency (size of visual detail)





Weber Contrast - C_W

$$\frac{I - I_\mathrm{b}}{I_\mathrm{b}}$$

- I = luminance of the object (e.g., text)
- I_b =luminance of the background
- Interpretation:
  - $C_W > 0$:object is **brighter** than background
  - $C_W < 0$:object is **darker** than background

Michelson contrast

$$\frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}}$$

- Better for periodic patterns (so to study contrast sensitivity)

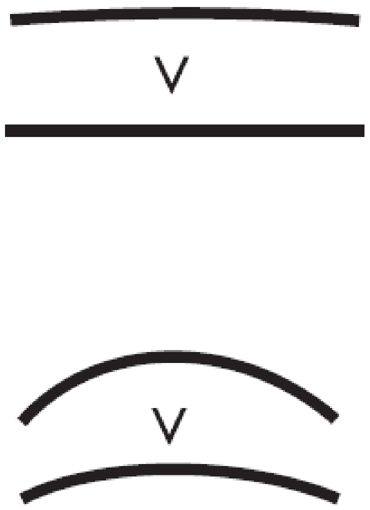
RMS contrast

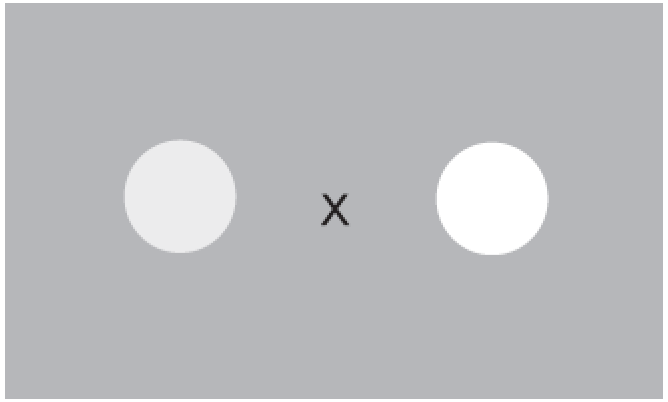
$$\sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(I_{ij}-\bar{I}\right)^2}$$

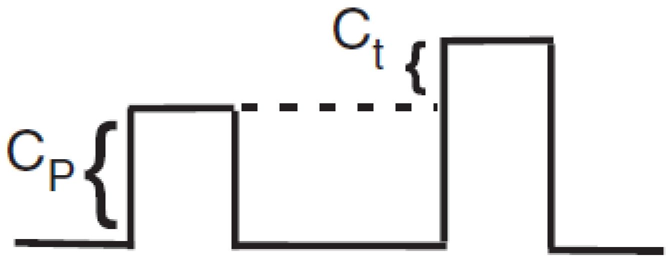
- For real-life stimuli
- Fo color stimuli, we need to sum up all colour channels as well

Detection vs discrimination

- Detection – we compare against zero incentive
- Discrimination – we compare against a non-zero stimulus
- Terminology is not clear

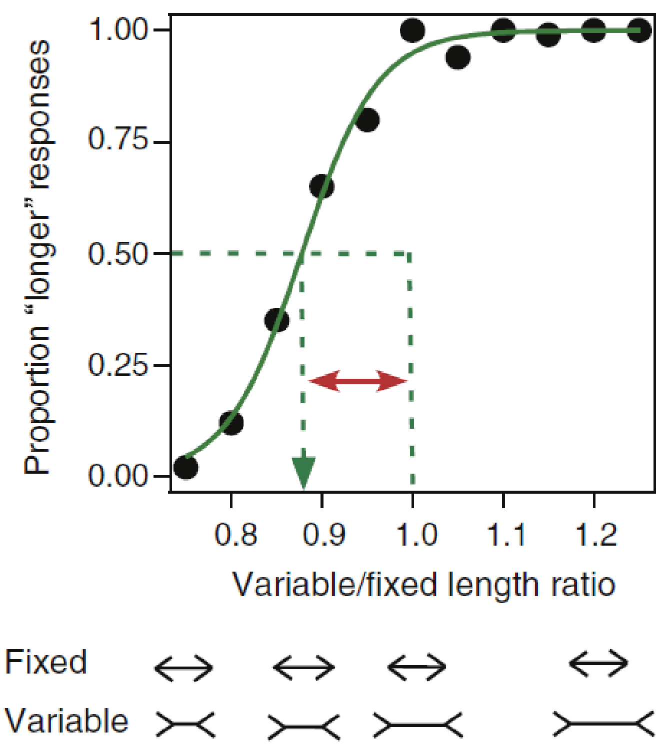






Threshold a suprathreshold

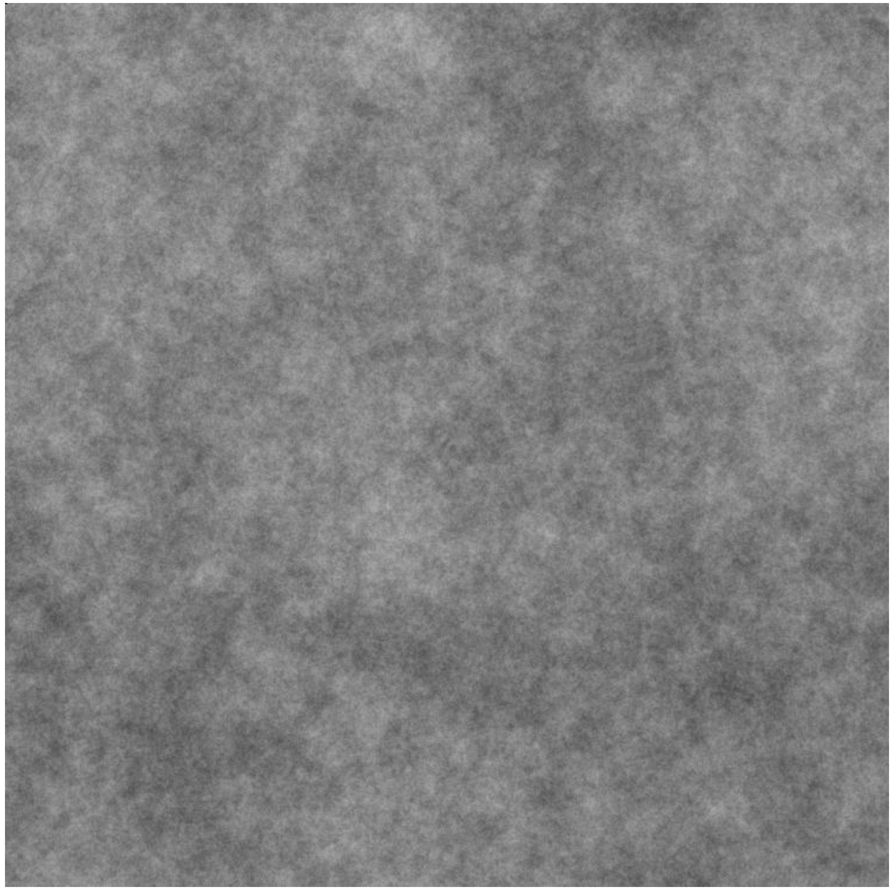
- Threshold – Threshold - when the state of perception changes from A to B
  - Absolute threshold – when are we able to detect the target at all
  - Relative threshold – difference change detection
- Suprathreshold – several definitions
  - Anything that does not measure threshold (i.e. contrast discrimination would not be suprathreshold)
  - Anything above the individual threshold (i.e. contrast discrimination would be contrast threshold)



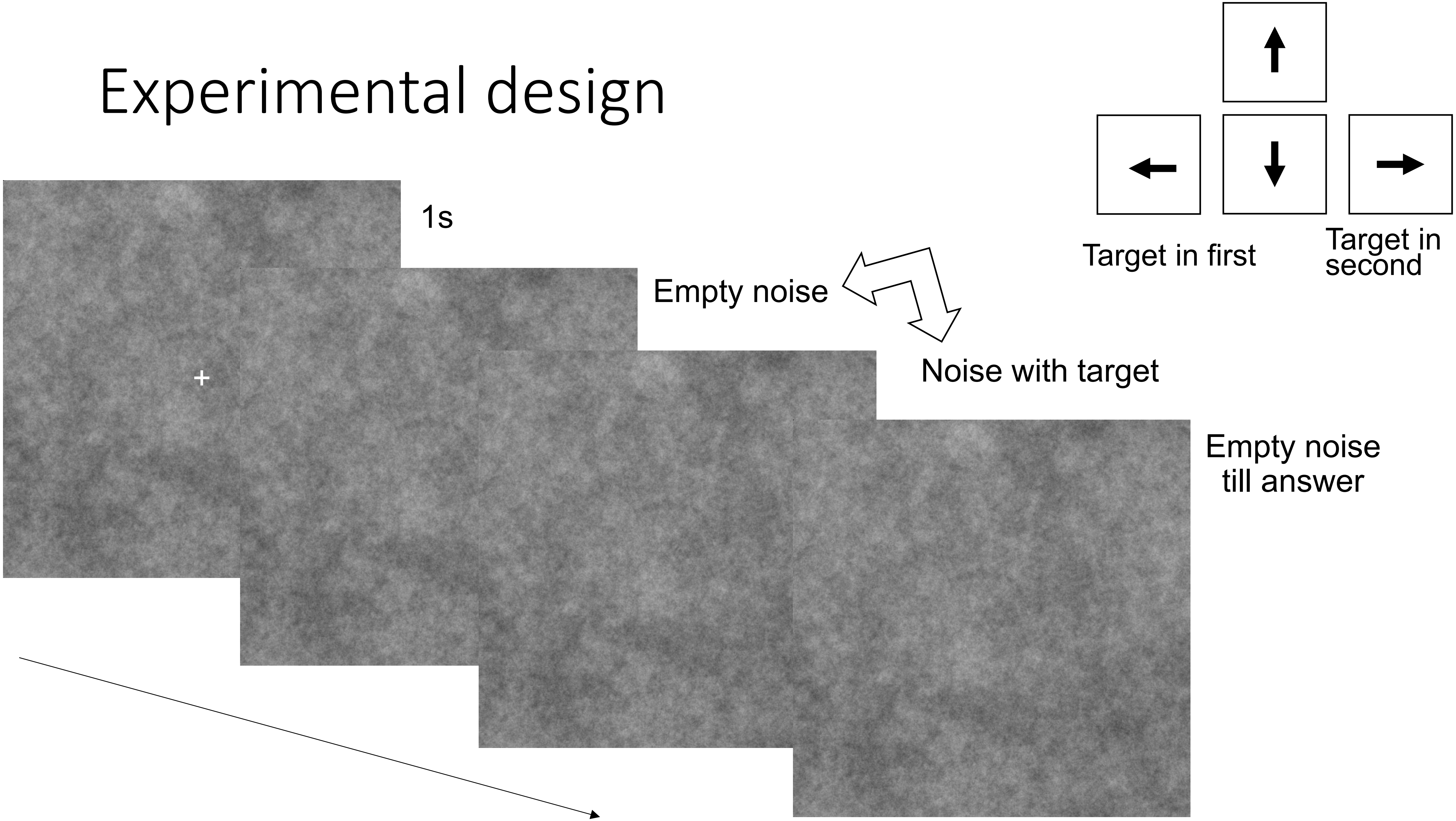
Psychometric function

- In the experiment, we show Gabor's patch in the noise

- We are working with very low intensities



Experimental design



Data

subject_id	trial_id	target contrast	target location	response	correct
1	1	0.04	first	first	1
1	2	0.02	first	second	0
1	3	0.08	second	second	1
1	4	0.02	first	first	1
1	5	0.16	second	second	1
1	6	0.08	first	second	0
1	7	0.16	second	second	1
1	8	0.04	second	first	0

Aggregated data

- We aggregate accuracies for individual levels

subject_id	target contrast	accuracy
1	0.02	58%
1	0.04	63%
1	0.08	78%
1	0.16	85%
1	0.32	95%

Visualization

- We are interested in threshold, here as stimulus level for 75% accuracy

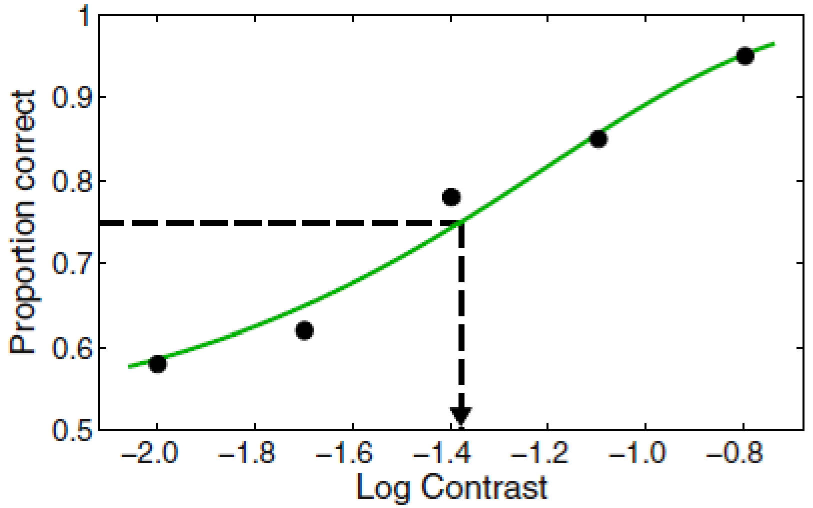


FIGURE 4.1 Example of a PF from a hypothetical experiment aimed at measuring a contrast detection threshold. The threshold is defined here as the stimulus contrast at which performance reaches a proportion correct equal to 0.75. Data are fitted using a log-Quick function.

How to describe the curve

- Usually 2 parameters
  - Threshold / PSE – intensity value where the state changes /when it subjectively looks the same to us
  - Slope – function growth rate (typically in the threshold)

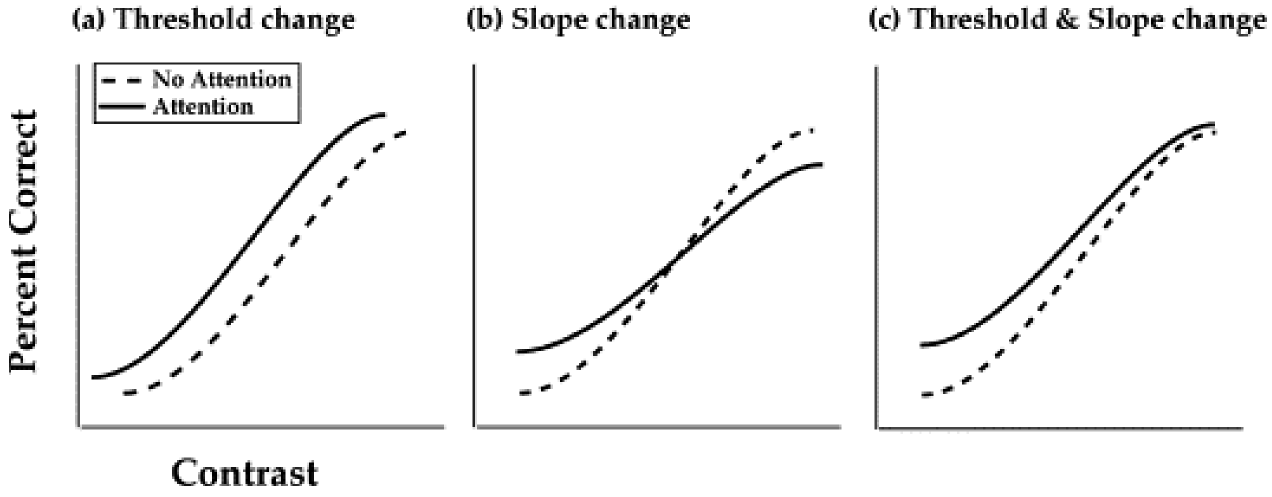
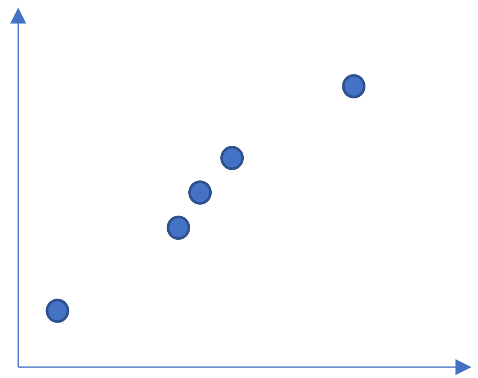


TABLE 4.1 Six values describing a fitted psychometric function

Threshold $\hat{\alpha}$	Slope $\hat{\beta}$	SE threshold	SE slope	Deviance	*p*-value
−1.3789	0.9079	0.0704	0.1582	1.1728	0.7652

What kind of data do we want

ideal



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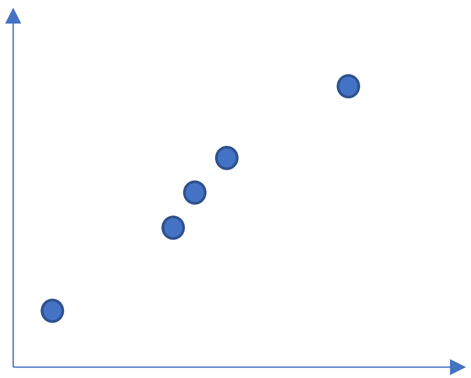
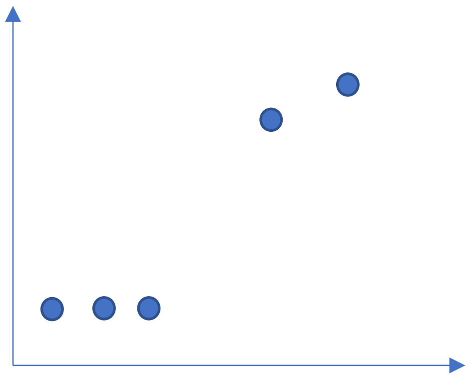


sort of



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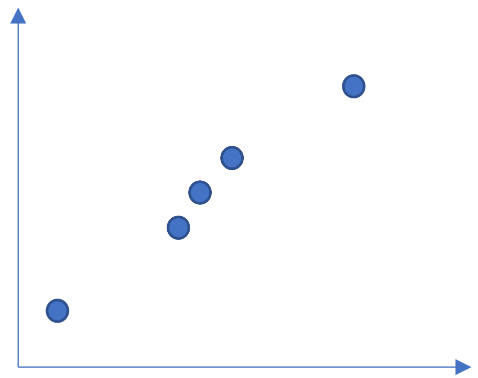
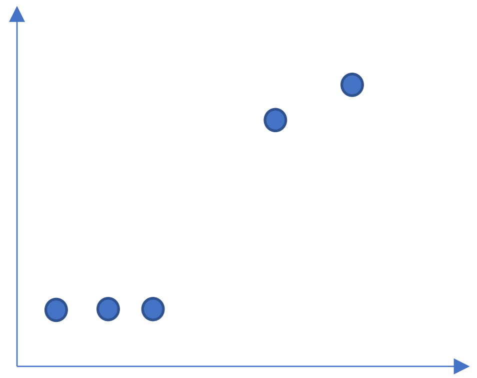
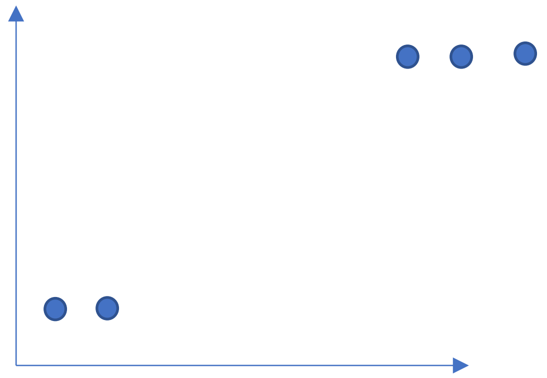


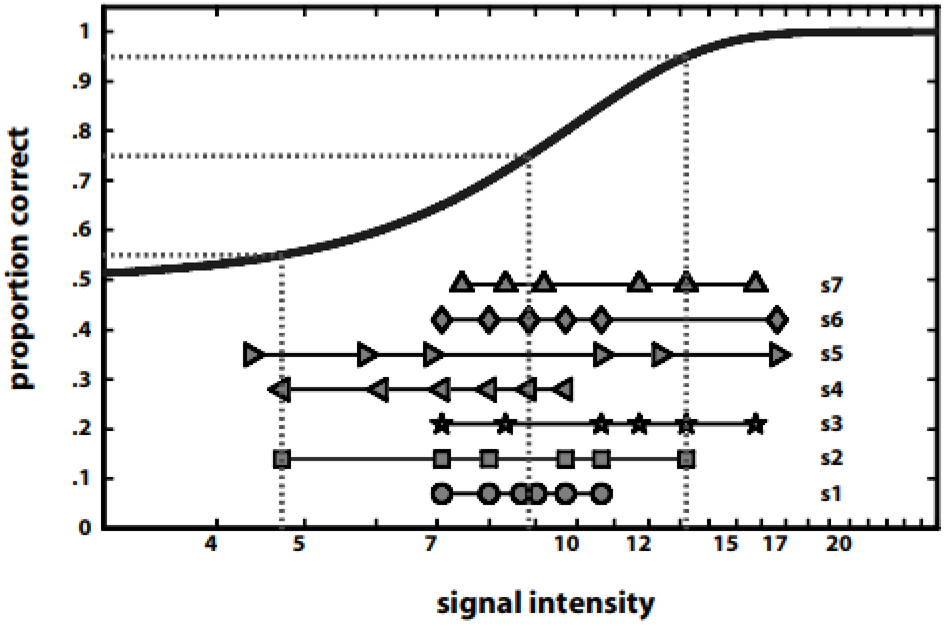
sort of



completely wrong



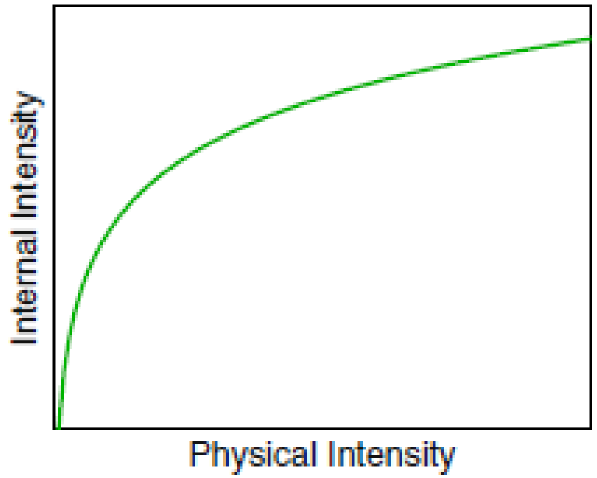
In evaluations of methods for PF



Amount of data and level of stimuli

R = f(S)

- Usually, we want data around threshold
- Approximate 400 trials per subject
  - 5 levels
  - 80 trials per level
- Transducer function
  - Function converting real intensity and subjective intensity
- Usually logarithmical scale



Number of levels

$$x_i = 10^{[\log a+(i-1)\log(b/a)/(n-1)]}$$

Lower limit

Upper limit

Dipper function (in contrast detection)

- Not all transducer look the same

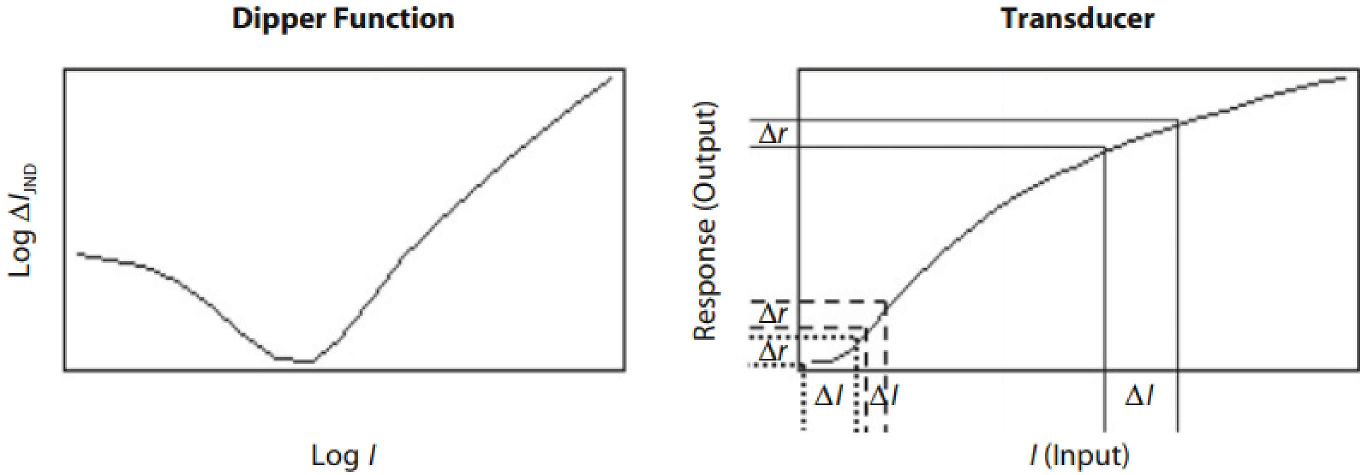


Figure 6. Nonlinear transduction. The transducer panel on the right shows the relationship between stimulus magnitude (on an arbitrary dimension) and the response of one sensory mechanism. In general, two stimuli can be discriminated if and only if the responses they elicit differ by more than some criterion Δr. Negative masking (indicated by the dipper function on the left) happens whenever the sensory response increases faster than the stimulus magnitude. Consider what happens when the pedestal is zero: The just noticeable difference (JND) for detection is represented as the distance between the two vertical dotted lines. The vertical dashed lines are closer together, and thus the JND for small pedestals is smaller. Because the thin solid lines are farther apart, the JND for large pedestals is larger.

Solomon, J. A. (2009). The history of dipper functions. *Attention, Perception, & Psychophysics*, *71*(3), 435-443.

Dipper function

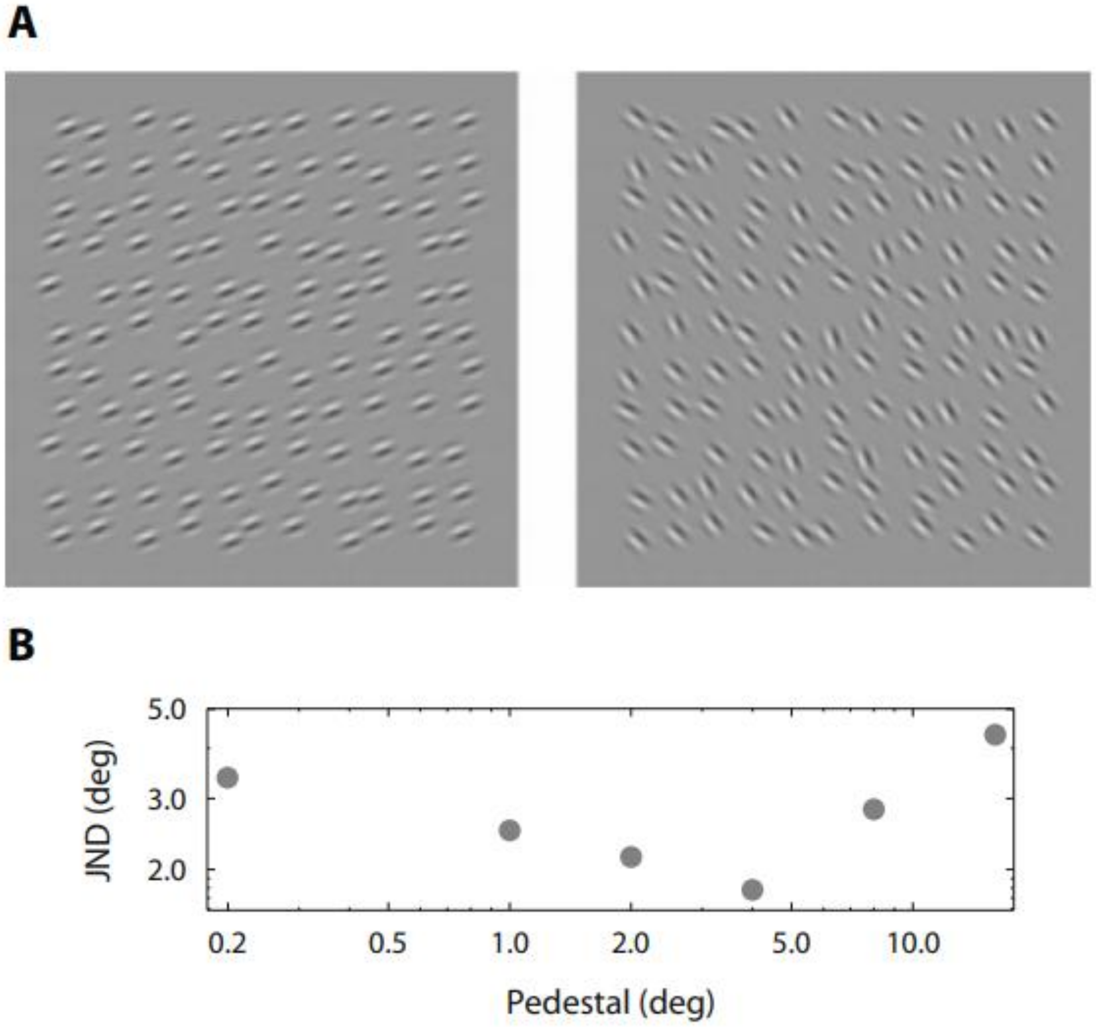


Figure 2. Example stimuli and example results from Morgan et al. (2008). The observers' 2AFC task was to report which of two images had higher variability in orientation. In the example here (panel A), there is zero variability in the image on the left. Orientations on the right were sampled from a Gaussian distribution with an 8º standard deviation. Each point in panel B shows observer M.M.'s (82% correct) just noticeable difference (JND) in the standard deviation.

Solomon, J. A. (2009). The history of dipper functions. *Attention, Perception, & Psychophysics*, *71*(3), 435-443.

Types of functions

- Several types of functions
- Specific function is selected based on:
  - theory
  - „nicely fits data“

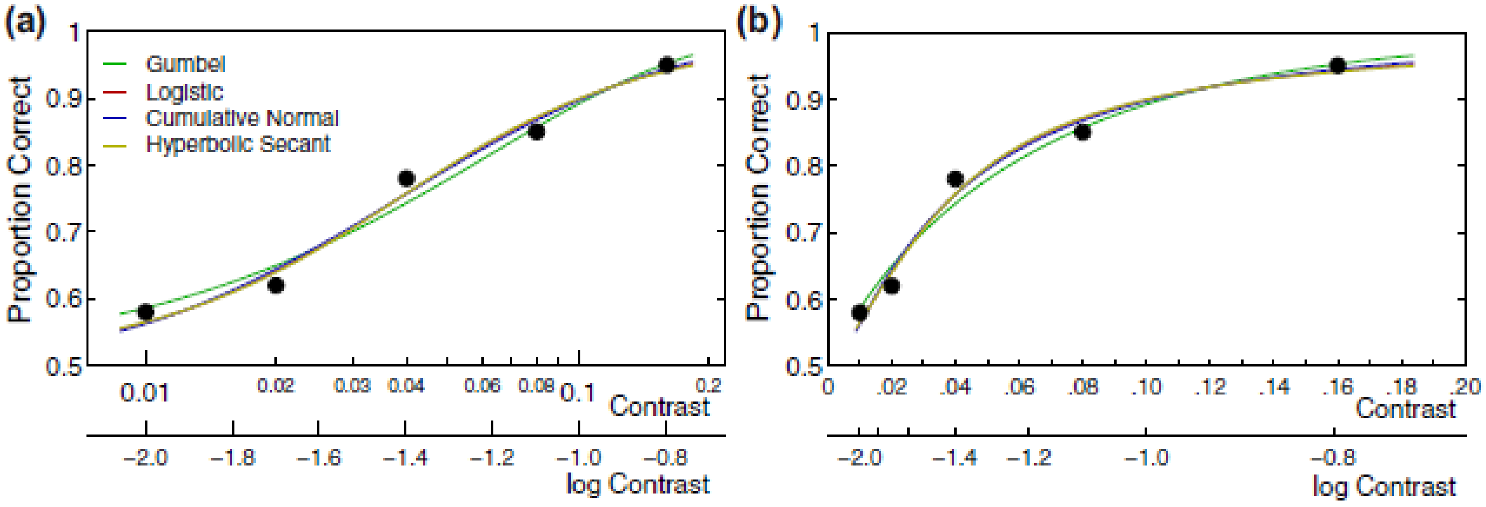


FIGURE 4.3 Example fits of four different PF functions. In (a) stimulus contrast is logarithmically spaced and in (b) contrast is linearly spaced.

How to describe curve + human behaviour

- Usually 4 parameters
  - Threshold / PSE – intensity value where the state changes /when it subjectively looks the same to us
  - Slope – function growth rate (typically in the threshold)
  - Guess rate – γ, what is the probability of success in guessing
  - Lapse rate – λ, procentage of trials, in which participant makes incorrect response

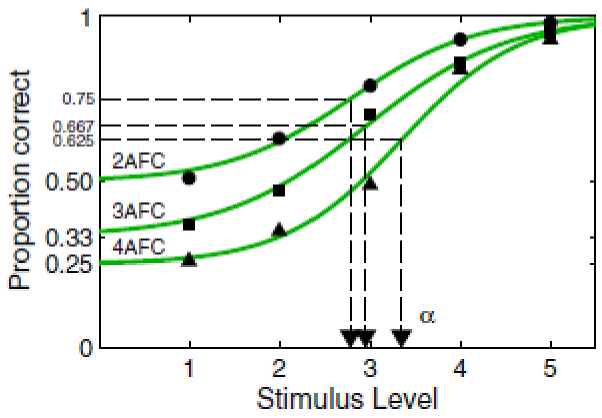


FIGURE 4.4 Example PFs for a 2AFC, 3AFC, and 4AFC task. A Logistic function has been fit to each set of data by using a different value for the guessing parameter, γ (0.5, 0.33, and 0.25, respectively). The lapse rate λ was set to 0 for all three. The threshold α corresponds to proportion correct of 0.75, 0.667, and 0.625, respectively.

PF for appearance tasks

- Guessing rate is not useful -> functions go from zero
- We are not looking for threshold, but point of subjective equivalence (PSE) – when both states seem equal
- Sometimes, y axis is on scale -1 to 1 (0 is PSE) – but this for reporting only, data must be fitted with values 0-1

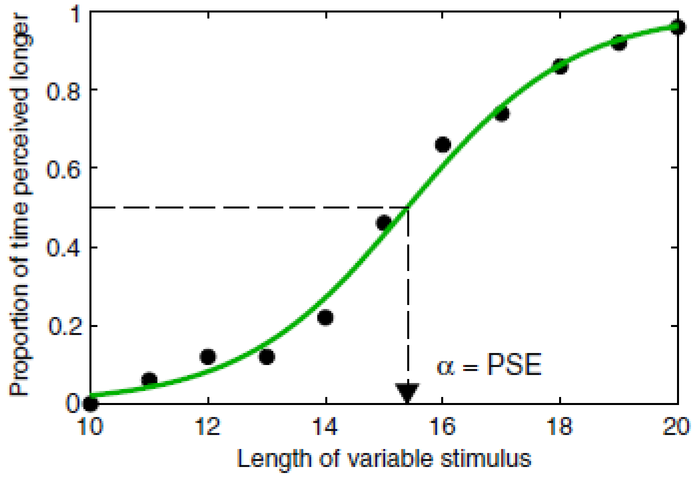


FIGURE 4.5 PF for an appearance-based task.

Theory behind PF

- If x is the stimulus intensity, $\psi(x)$ is the performance for stimulus x
- We're not as interested in performance as we are in the internal sensory response $F(x; \theta)$, where θ are the parameters of the function
- $F(x; \theta)$ we can't measure directly, only $\psi(x)$
- Two theories HTT and SDT

High threshold theory

- 2IFC experiment, Signal S and noise N
- abstraction: we have specialized neurons in brain reacting on S (like a Gaussian distribution)
- N also produces signal, distance is linear with respect to intensity
- We have an internal threshold, and if the sensory signal exceeds it, I'll register it
- I don't know how strong the signal was unless it reaches the threshold

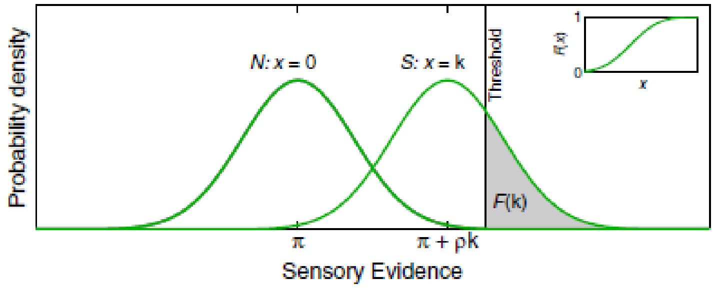


FIGURE 4.6 High-Threshold Theory and the PF.

HTT – guessing rate and lapse rate

- If I don't reach the threshold, I have to guess (guessing rate)
- Lapse rate – probability of making an error (in theory two types)
  - Sensory inattention
  - Motor error
- Relationship between $\psi(x; \alpha,\beta,\lambda,\gamma)$ and $F(x;\alpha,\beta)$

Breakdown of answers

$$\psi(x;\alpha,\beta,\gamma,\lambda^*) = \gamma + (1-\gamma-\lambda^*+\lambda^*\gamma)F(x;\alpha,\beta)$$

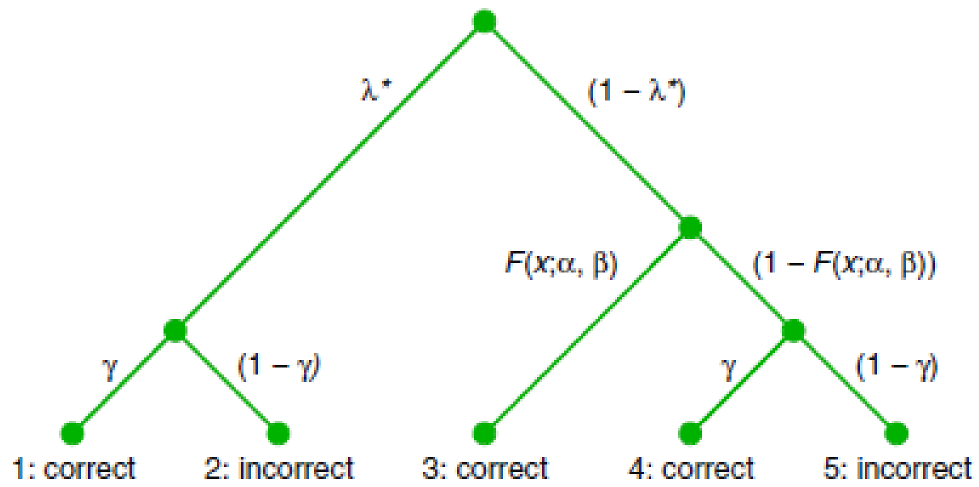


FIGURE 4.7 Relation between $F(x;\alpha,\beta)$ and $\psi(x;\alpha,\beta,\gamma,\lambda)$ according to high-threshold theory.

More common version

- Lapse can also occur when guessing
- So we define λ = λ*(1 – γ)
- λ – probability that the proband will make a mistake
- λ*- motor error

- If a proband sneezed every tenth trial during 2AFC:
  λ = 0.1(1 – 0.5) = 0.05

$$\psi(x;\alpha,\beta,\gamma,\lambda^*) = \gamma + (1-\gamma-\lambda^* + \lambda^*\gamma)F(x;\alpha,\beta)$$

$$\psi(x;\alpha,\beta,\gamma,\lambda) = \gamma + (1-\gamma-\lambda)F(x;\alpha,\beta)$$

Range of PF

- 1-λ is upper assymptote, γ is lower asymptote

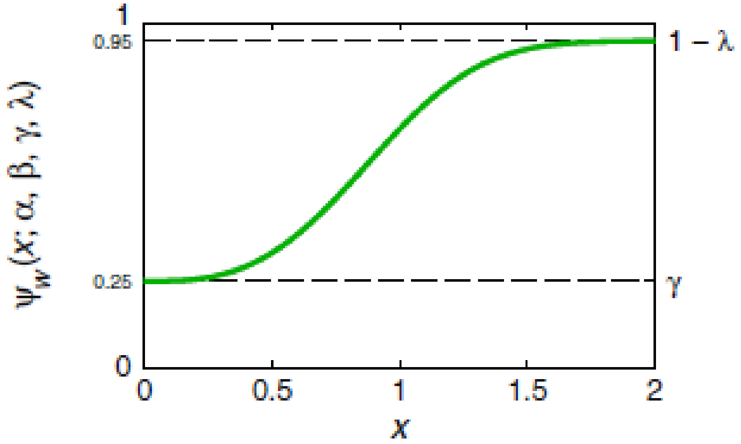


FIGURE 4.8 $\psi_W(x; \alpha, \beta, \gamma, \lambda)$, where F is modeled by the Weibull function $F_W(x; \alpha, \beta)$, threshold $\alpha = 1$, slope $\beta = 3$, guess rate $\gamma = 0.25$, and lapse rate $\lambda = 0.05$.

PF according SDT

- SDT does not have fixed threshold,so we need to take into account both signal and noise
- Every trial, we randomly select answer from N and S distribution and we answer based on higher value
- Difference is also normály distributed

Upper part of cumulative normal function -> different transducer is required

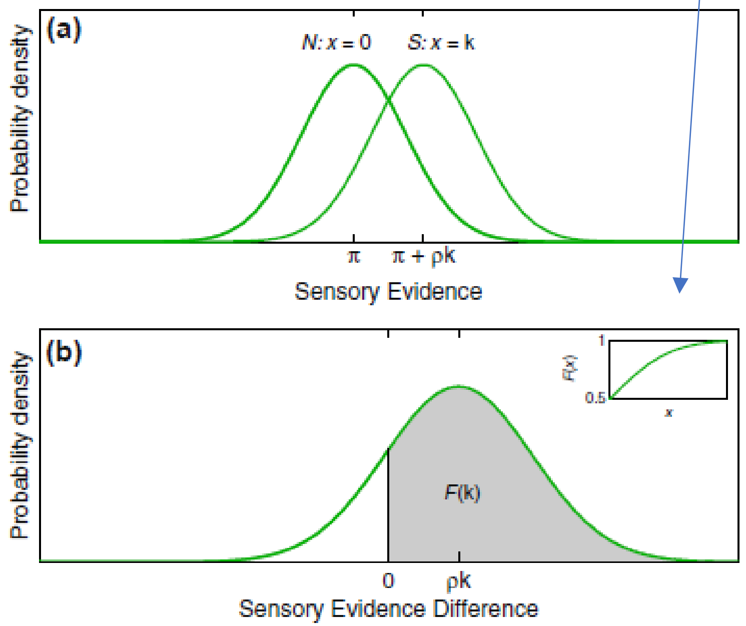


FIGURE 4.9 The relation between SDT and the PF. (a) Probability density functions for the sensory evidence obtained in the noise (N) and stimulus (S) intervals and (b) probability density function for the difference in sensory evidence obtained between the N and S intervals.

PF according SDT

- Observer never guess! $$\psi(x;\alpha,\beta,\gamma,\lambda) = \gamma + (1-\gamma-\lambda)F(x;\alpha,\beta)$$
- Shape of function makes sense for SDT, but γ has different meaning
- Nowadays SDT is commonly used, but we use guessing rate and threshold from HTT
- Correct way would be: *The amount of sensory evidence accumulated while sampling from the signal presentation happened to exceed the amount of sensory evidence accumulated while sampling from the noise presentation*
- But we say: Observer guessed an answer.

What functions can we use?

- We can use several functions for F(x; α,β)
  - Cumulative normal distribution function
  - Logistic function
  - Weibull
  - Gumbel
  - Quick/Log-Quick
  - Hyperbolic Secant $F_{HS}(x;\alpha,\beta) = \frac{2}{\pi}\tan^{-1}\exp\left(\frac{\pi}{2}\beta(x-\alpha)\right)$
  - Our own..

Cumulative normal

$x \in (-\infty,\ +\infty),\ \alpha \in (-\infty,\ +\infty),$ and $\beta \in (0,\ +\infty)$

$$F_N(x; \alpha, \beta) = \frac{\beta}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(-\frac{\beta^2(x-\alpha)^2}{2}\right)$$

No closed form

- Makes sense according to theory

- α – corresponds to thresholdu ($F_N(x = \alpha; \alpha, \beta) = 0.5$)
- β – corresponds to slope

- If x=0 means absence of signal, this can be used x is log-transformed

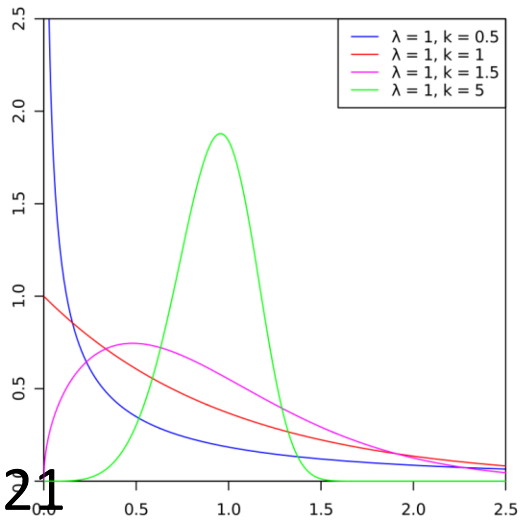
Logistic function

- α – corresponds to threshold ($F_N(x = \alpha; \alpha, \beta) = 0.5$
- β – corresponds to threshold
- It is an approximation of CNF ($\beta_L \approx 1.7/\beta_N$)
- Advantage over CNF is existence of closed form
- Again problem with x=0

$$F_L(x; \alpha, \beta) = \frac{1}{1 + \exp(-\beta(x - \alpha))}$$

$x \in (-\infty, +\infty)$, $\alpha \in (-\infty, +\infty)$, and $\beta \in (0, +\infty)$

Weibull and Gumbel function



- Weibull
  - α – corresponds to threshold ($F_N(x = \alpha; \alpha, \beta) = 1\text{-exp}(-1) \approx 0.6321$
  - β – corresponds to threshold (but also depends on α)
    - change in α leads to change in slope, even when β is constant

$$F_W(x; \alpha, \beta) = 1 - \exp\left(-\left(\frac{x}{\alpha}\right)^{\beta}\right)$$

$x \in [0, +\infty)$, $\alpha \in (0, +\infty)$, and $\beta \in (0, +\infty)$.

  - Not for log scale, as x ≥ 0
- Gumbel (log-Weibull)
  - Like Weibull, but on logarithmic scale

$$F_G(x; \alpha, \beta) = 1 - \exp\left(-10^{(\beta(x-\alpha))}\right)$$

$x \in (-\infty, +\infty)$, $\alpha \in (-\infty, +\infty)$, and $\beta \in (0, +\infty)$

Quick a Log-Quick

- Quick

$$F_Q(x;\alpha,\beta) = 1 - 2^{\left(-\left(\frac{x}{\alpha}\right)^{\beta}\right)}$$

  - Here is threshold 0.5

- Log-Quick

$$F_{lQ}(x;\alpha,\beta) = 1 - 2^{\left(-10^{(\beta(x-\alpha))}\right)}$$

  - Again log version of Quick

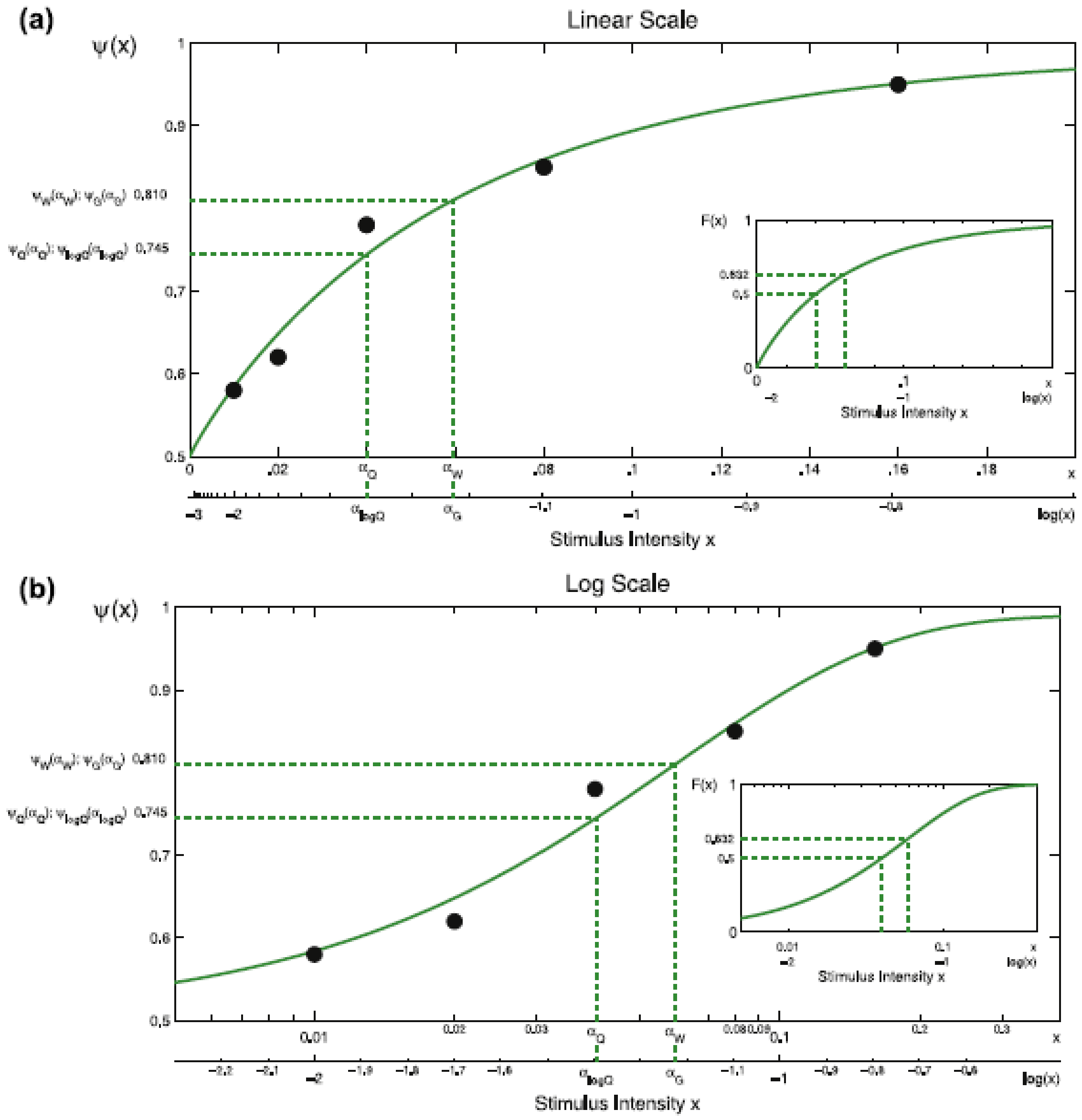
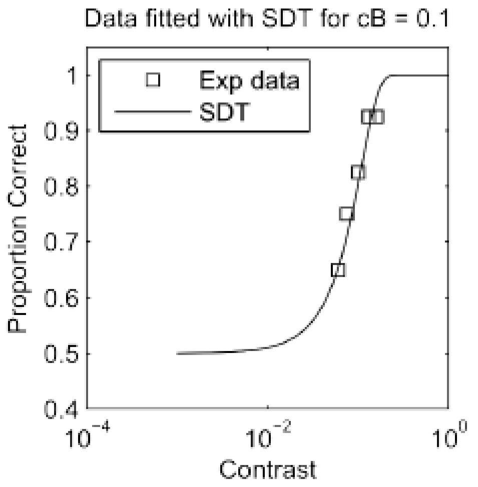


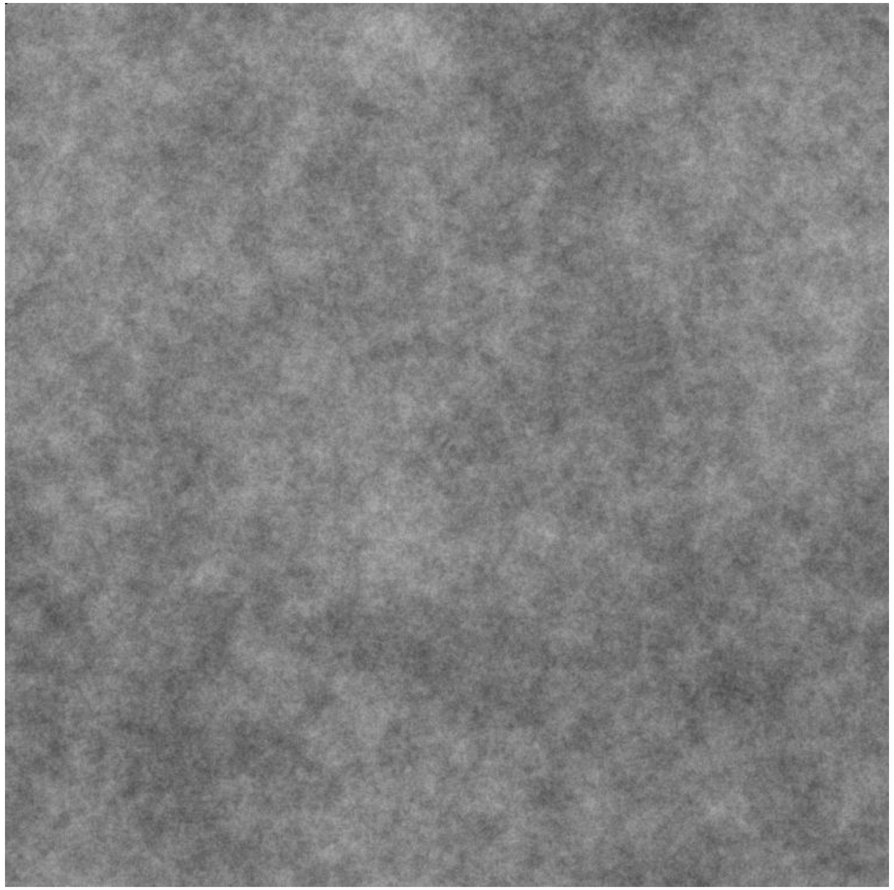
FIGURE B4.5.1 The relationships among the PFs in the Weibull family: Weibull, Gumbel, Quick, and log-Quick functions. Functions are plotted on linear scale (a) as well as logarithmic scale (b).

Custom function

- If we have correct theory, we can create PF based on that



$$P_{corr}(c; c_T, \beta) = \Phi(0.5 \cdot (\frac{c}{c_T})^{\beta})$$



PF and variance

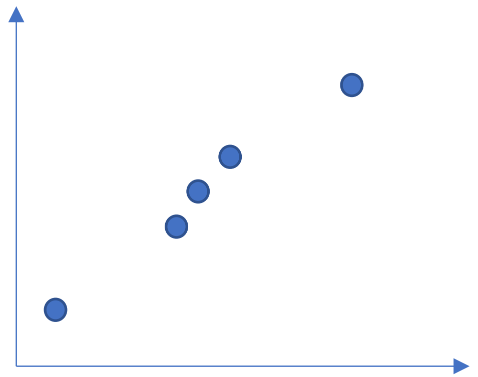
- Because β is not transferable between functions (β=2 in CNF means steeper slope than β=2 in logistic)

- Ve take some predefined range of data

$$\sigma = \psi^{-1}(1 - \lambda - \delta; \alpha, \beta, \gamma, \lambda) - \psi^{-1}(\gamma + \delta; \alpha, \beta, \gamma, \lambda).$$

How to find the best curve?

- Maximum likelihood estimate (MLE)
- Likelihood: P(data|θ), where θ are free parameters)
  - Dat are fixed – compare with probability, where we try to predict the data
- Used as a common tools to estimate parameters



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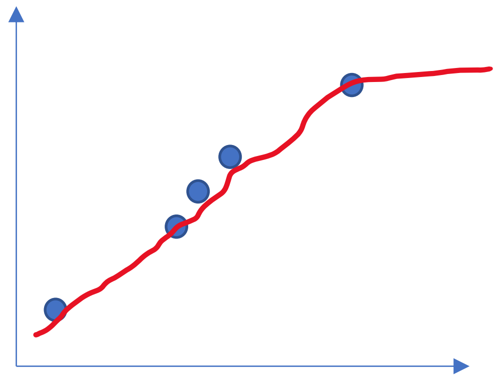

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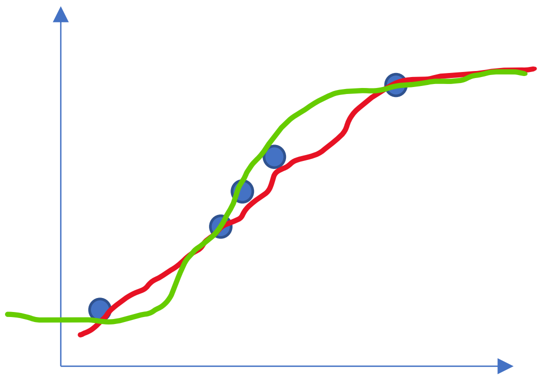
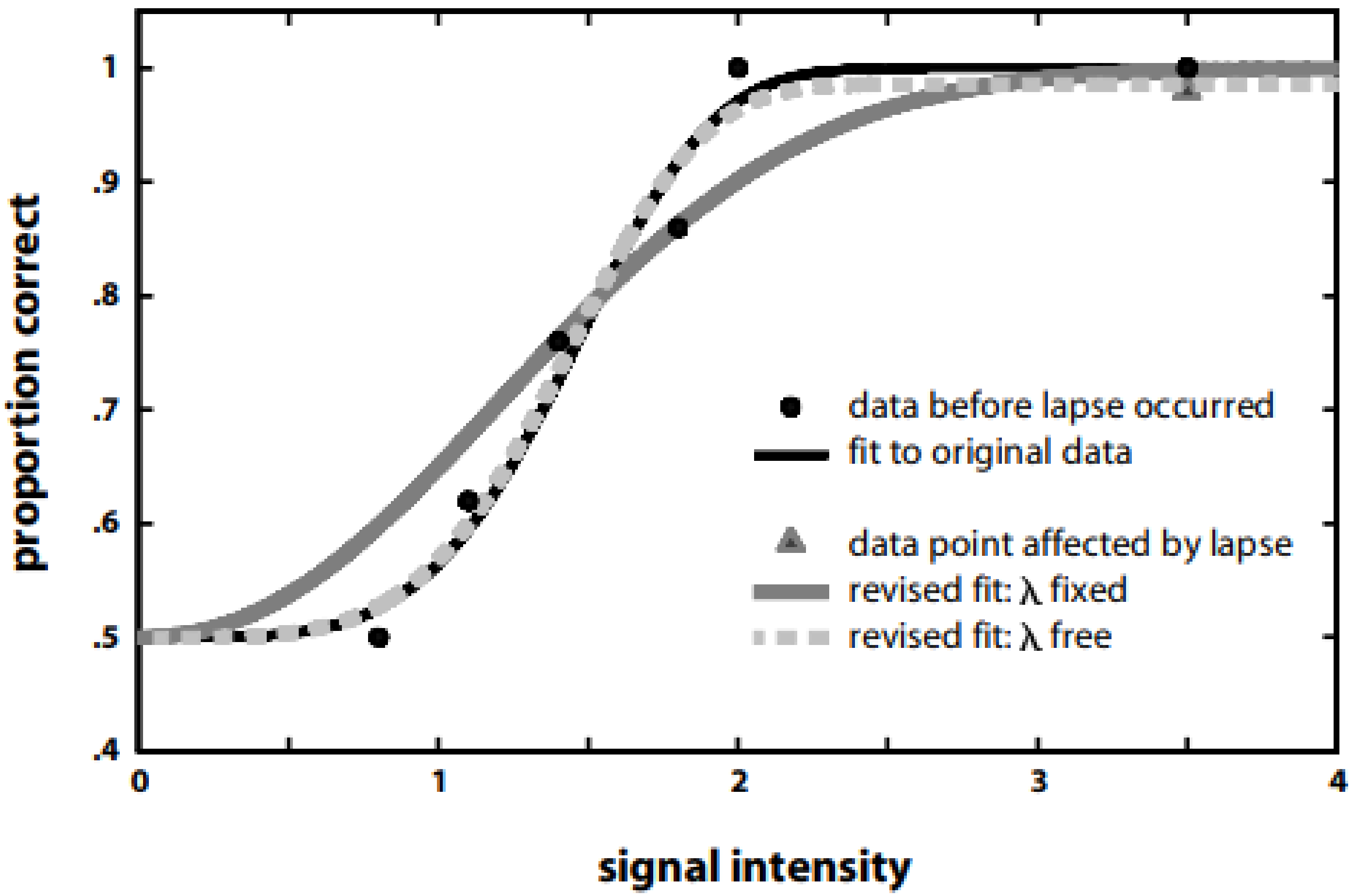


Lapse rate can change the fit

- Lapse rate is a problem for upper asymptote
- Alternative:

$$\psi(x) = \gamma + (1 - \gamma - \lambda)F(x\,; \alpha, \beta) \qquad \text{when} \quad x < \text{APL}$$
$$\psi(x) = 1 - \lambda \qquad \text{when} \quad x = \text{APL},$$



When fit is not good

- It is important to have good stimuli levels

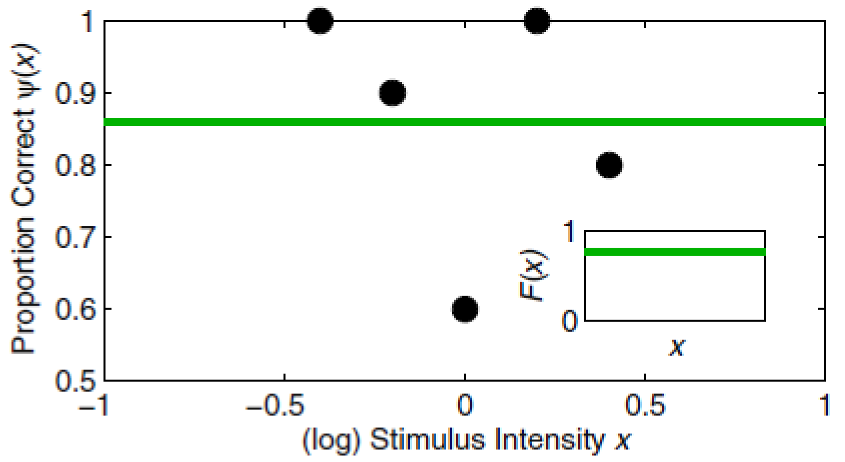


FIGURE B4.7.4 The green line shows a Gumbel function with threshold equal to −4550.9613 and slope equal to 0.000035559, guess rate equal to 0.5, and lapse rate equal to 0.03. Within the stimulus range shown, it is asymptotically near a horizontal line at 0.86, the best fit to these data that can be obtained under the constraint that a Gumbel function is to be fit. See text for details.

How to do it practically?

- R
  - Quickpsy - https://dlinares.org/quickpsy.html
  - Brms - https://medium.com/@marc.jacobs012/modelling-psychophysical-functions-70ca69d18b87

- Jamovi
  - Jmvquickpsy - https://github.com/visionlabels/jmvquickpsy

Modern approaches

Journal of Vision (2012) 12(11):26, 1–17 http://www.journalofvision.org/content/12/11/26 1

Modeling psychophysical data at the population-level: The generalized linear mixed model

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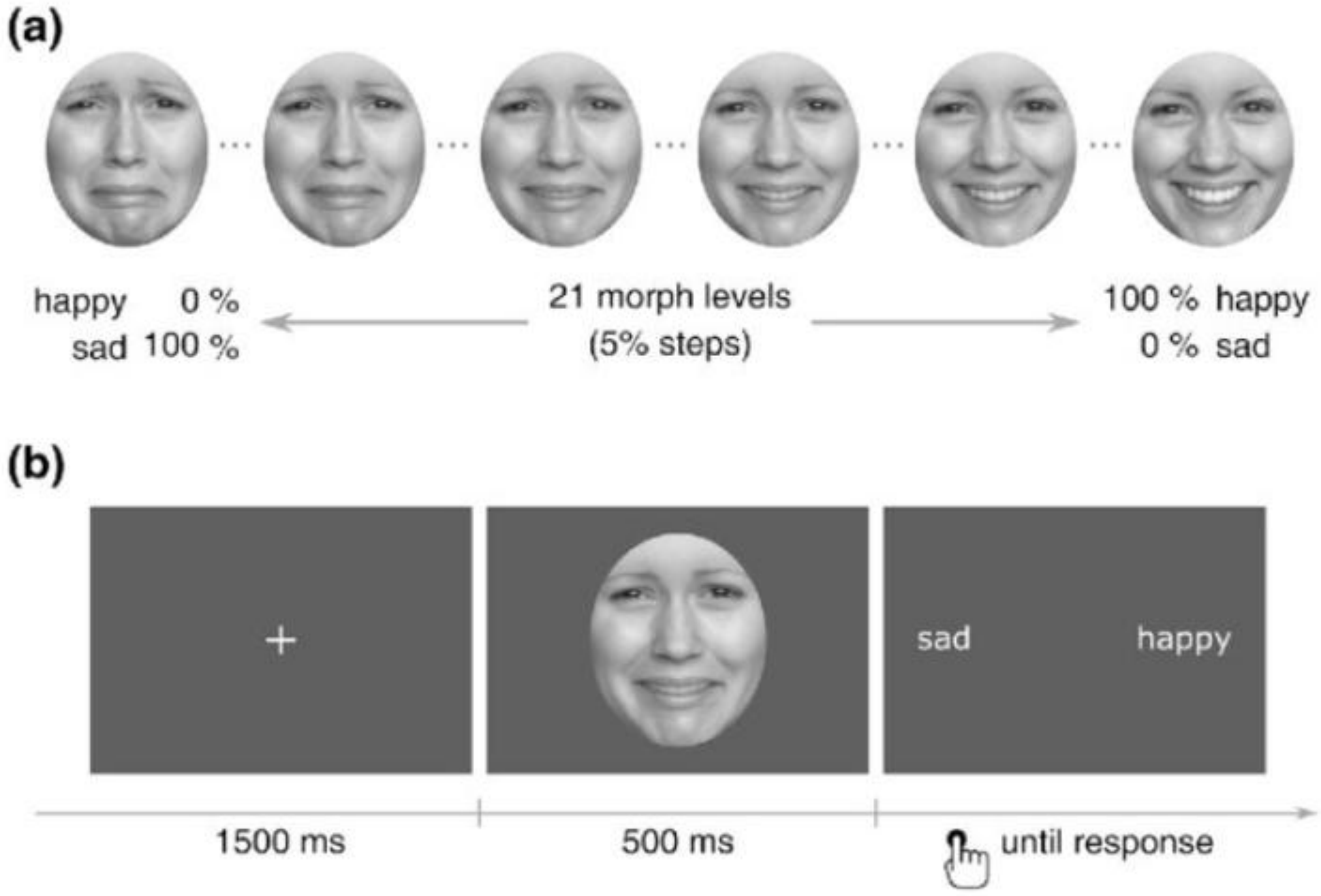
In psychophysics, researchers usually apply a two-level model for the analysis of the behavior of the single subject and the population. This classical model has two main disadvantages. First, the second level of the analysis discards information on trial repetitions and subject-specific variability. Second, the model does not easily allow assessing the goodness of fit. As an alternative to this classical approach, here we propose the Generalized Linear Mixed Model (GLMM). The GLMM separately estimates the variability of fixed and random effects, it has a higher statistical power, and it allows an easier assessment of the goodness of fit compared with the classical two-level model. GLMMs have been frequently used in many disciplines since the 1990s; however, they have been rarely applied in psychophysics. Furthermore, to our knowledge, the issue of estimating the point-of-subjective-equivalence (PSE) within the GLMM framework has never been addressed. Therefore the article has two purposes: It provides a brief introduction to the usage of the GLMM in psychophysics, and it evaluates two different methods to estimate the PSE and its variability within the GLMM framework. We compare the performance of the GLMM and the classical two-level model on published experimental data and simulated data. We report that the estimated values of the parameters were similar between the two models and Type I errors were below the confidence level in both models. However, the GLMM has a higher statistical power than the two-level model. Moreover, one can easily compare the fit of different GLMMs according to different criteria. In conclusion, we argue that the GLMM can be a useful method in psychophysics.

Keywords: Generalized Linear Mixed Model, two-level analysis, psychophysics, statistical power

Citation: Moscatelli, A., Mezzetti, M., & Lacquaniti, F. (2012). Modeling psychophysical data at the population-level: The generalized linear mixed model. *Journal of Vision, 12*(11):26, 1–17, http://www.journalofvision.org/content/12/11/26, doi:10.1167/12.11.26.

Example dataset



Demonstration of psychophysics in practice

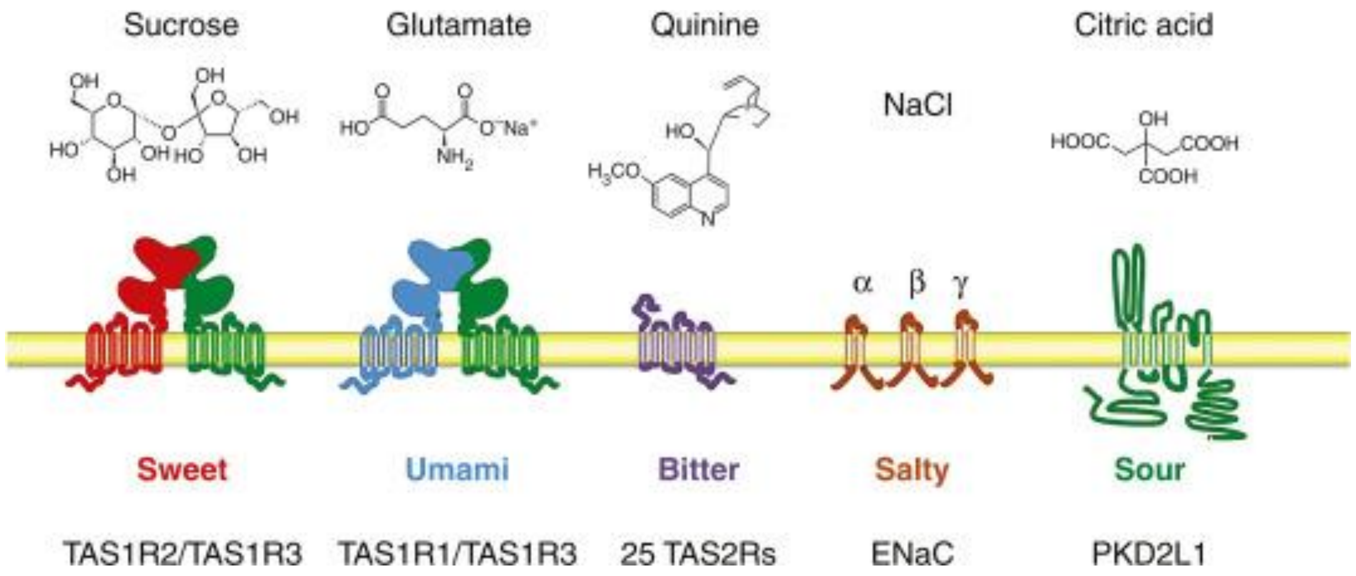
Rejection Thresholds in Solid Chocolate-Flavored Compound Coating

Meriel L. Harwood, Gregory R. Ziegler, and John E. Hayes

Abstract: Classical detection thresholds do not predict liking, as they focus on the presence or absence of a sensation. Recently however, Prescott and colleagues described a new method, the rejection threshold, where a series of forced choice preference tasks are used to generate a dose-response function to determine hedonically acceptable concentrations. That is, how much is too much? To date, this approach has been used exclusively in liquid foods. Here, we determined group rejection thresholds in solid chocolate-flavored compound coating for bitterness. The influences of self-identified preferences for milk or dark chocolate, as well as eating style (chewers compared to melters) on rejection thresholds were investigated. Stimuli included milk chocolate-flavored compound coating spiked with increasing amounts of sucrose octaacetate, a bitter and generally recognized as safe additive. Paired preference tests (blank compared to spike) were used to determine the proportion of the group that preferred the blank. Across pairs, spiked samples were presented in ascending concentration. We were able to quantify and compare differences between 2 self-identified market segments. The rejection threshold for the dark chocolate preferring group was significantly higher than the milk chocolate preferring group ($P = 0.01$). Conversely, eating style did not affect group rejection thresholds ($P = 0.14$), although this may reflect the amount of chocolate given to participants. Additionally, there was no association between chocolate preference and eating style ($P = 0.36$). Present work supports the contention that this method can be used to examine preferences within specific market segments and potentially individual differences as they relate to ingestive behavior.

Keywords: bitterness, food preference, methodology, psychophysics, rejection threshold

Types of flavours



Someone likes it bitter!

- Detection threshold
  vs Rejection threshold

- The problem with detection is that knowing the threshold gives us a wrong description of the suprathreshold
- In other words, how much bitterness is too much?

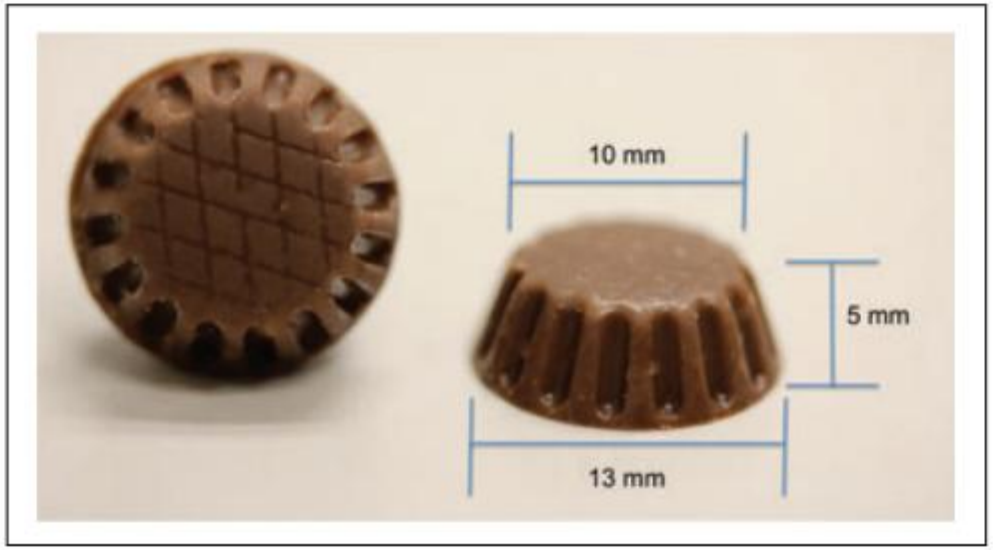


Figure 1–Sample dimensions. (1) Shape and measurements: one sample piece is shown from above and another is shown from a side-view with references for the dimensions of the samples, which are 10 mm x 13 mm x 5 mm. Each sample piece was approximately 0.63 g.

How we eat chocolate

- They had the participants eat chocolate and measured via EGG (vocal cord measurement) and EMG (tongue muscle activity measurement)
- They then performed a cluster analysis
- Typology of chocolate consumers
  - Fast chewers – they chew and swallow quickly
  - Thorough chewers – thoroughly chew
  - Suckers

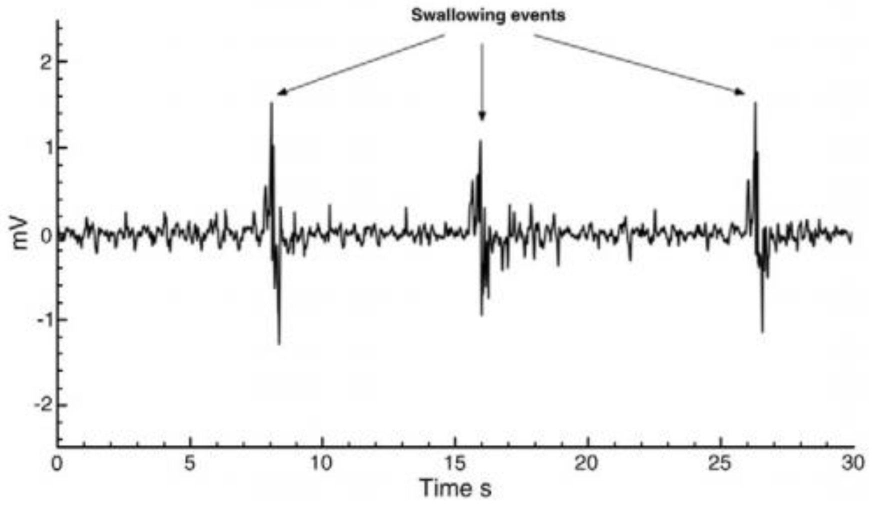


Fig. 4. Electroglottography (EGG) trace from a subject eating a sample of chocolate A.

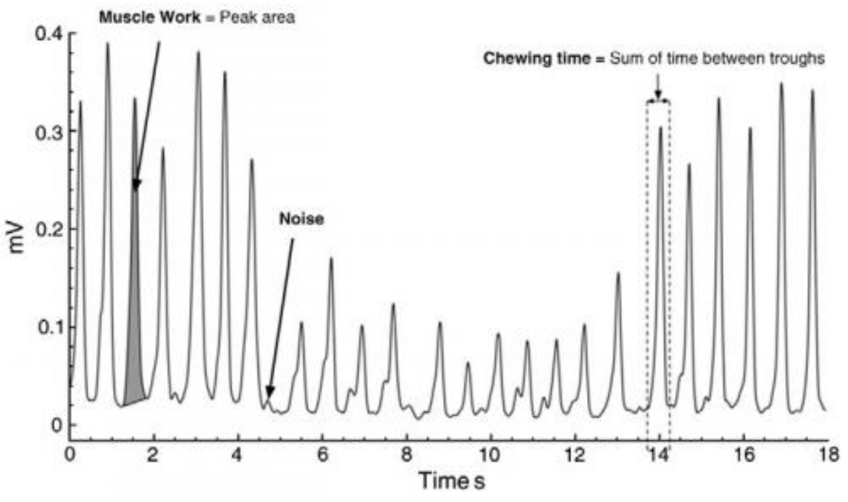


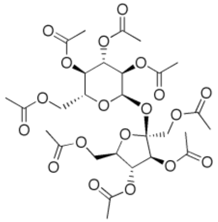
Fig. 2. Electromyography (EMG) trace from left masseter muscle while subject is eating a sample of chocolate A.

Carvalho-da-Silva, A. M., Van Damme, I., Wolf, B., & Hort, J. (2011). *Characterisation of chocolate eating behaviour. Physiology & Behavior, 104(5), 929–933.* doi:10.1016/j.physbeh.2011.06.001

Method

+

Sucrose octacetate



SOA
(simulate bitterness)

0 µM

7.5 µM

15 µM

30 µM

60 µM

120 µM

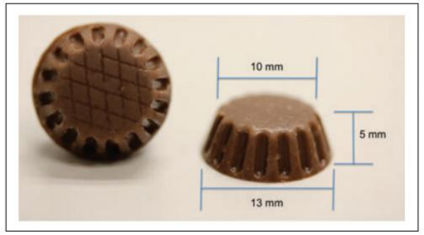


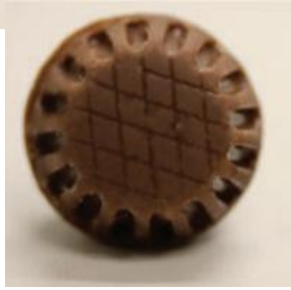
Figure 1–Sample dimensions. (1) Shape and measurements: one sample piece is shown from above and another is shown from a side-view with references for the dimensions of the samples, which are 10 mm × 13 mm × 5 mm. Each sample piece was approximately 0.63 g.

Method 2

Which one do you prefer?

0 µM

x µM



0 µM

x µM

0 µM

x µM

Results

Table 1–Rejection thresholds by group.

Group	*n*	Rejection threshold (μM)	*P*-value
All participants	85	81.5	n/a
Milk chocolate preferring	43	43.9	0.011[a]
Dark chocolate preferring	42	113.5	
Thorough chewers	45	70.0	0.144
Quick chewers	8	–	
Melters	32	93.3	

[a]Statistically significant across the respective groups.

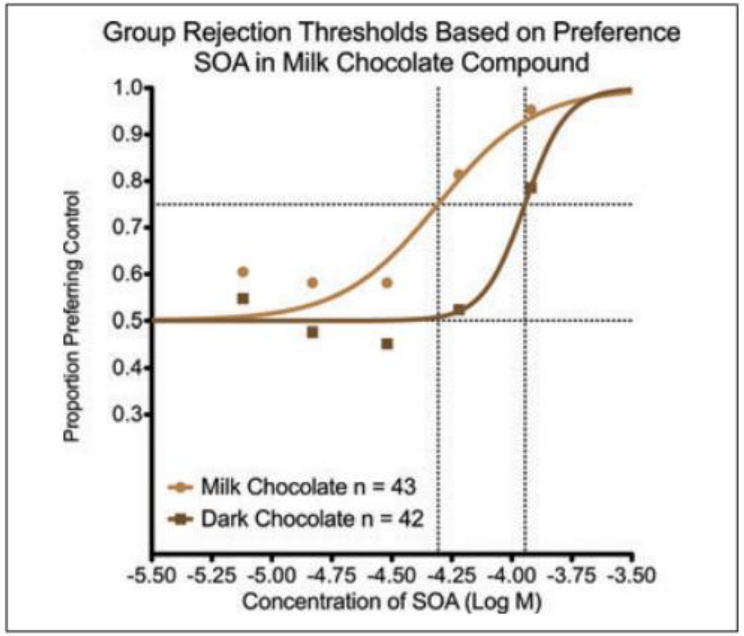


Figure 2–Group rejection thresholds based on preference for SOA in solid chocolate. Proportion of participants preferring the un-spiked samples is plotted against concentration of SOA in the spiked sample. The circles (light brown) represent individuals who prefer milk chocolate when eating solid chocolate; the squares (dark brown) represent those who prefer dark chocolate. The chance-corrected concentration at which 50% of participants preferred the control, the rejection threshold, was significantly higher for those who prefer dark chocolate ($P = .01$).

Problems

- What is and is not psychophysics in this study?

Psychological units of seriousness of crime

Bulletin of the Psychonomic Society
1982, Vol. 19(5), 275-278

Psychophysical measurement of the judged seriousness of crimes and severity of punishments

Question of scaling

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Hamilton College, Clinton, New York 13323

Ratio scaling techniques of magnitude estimation and cross-modality matching were used to establish psychological scales of the seriousness of 22 crimes and the severity of their associated punishments. The judged seriousness of crimes and judged severity of punishments were related to the physical duration of punishment by the same nonlinear function. Judged seriousness of crimes and severity of punishments were both power functions with an exponent of .5 of the duration of prison term. The results suggest that, in most cases, the punishment fits the crime when both are expressed in psychological units.

- What is a proper punishement for a given crime?
- Sellin and Wolfgang (1964) – Steven's power law with coef 0.7 – are these subjective ratings valid?

Gescheider, G. A., Catlin, E. C., & Fontana, A. M. (1982). Psychophysical measurement of the judged seriousness of crimes and severity of punishments. *Bulletin of the Psychonomic Society*, *19*, 275-278.

Table 1
Crimes and Associated Maximum Sentences (in Years in Jail)

	Sentence	Scale Value
Murder I	Life	23.5
Kidnapping I	Life	15.8
Arson I	25	13.2
Robbery I	25	11.5
Rape I	25	17.0
Forgery I	15	6.4
Assault I	15	13.2
Arson II	15	8.5
Perjury	7	5.1
Robbery III	7	5.6
Bribery for Public Office	7	6.3
Gambling I	4	3.0
Criminal Usury	4	5.2
Child Abandonment	4	12.3
Criminal Trespass II	1	1.7
Petit Larceny	1	3.7
Resisting Arrest	1	2.7
Issuing Bad Checks	.25	2.5
Disclosure of Grand Jury	.25	3.9
Misconduct of Corporate Official	.25	5.2
Harassment	.04	2.6
Prostitution	.04	1.2

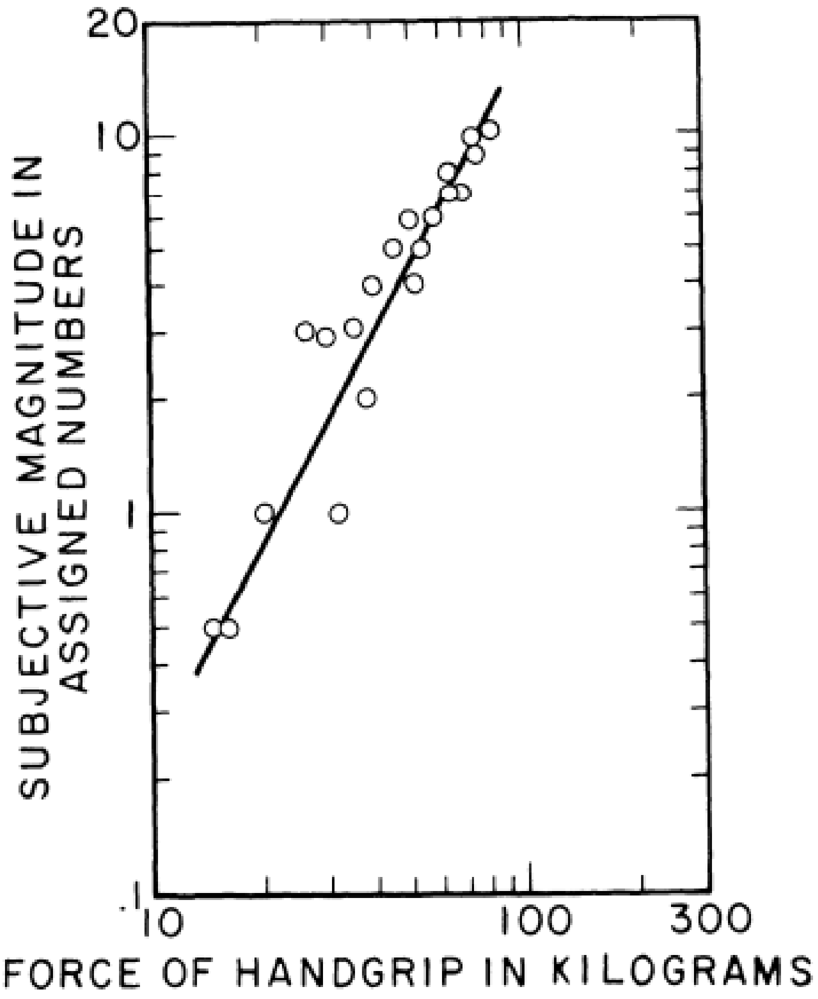


Figure 1. Magnitude estimations of subjective effort as a function of force of handgrip.

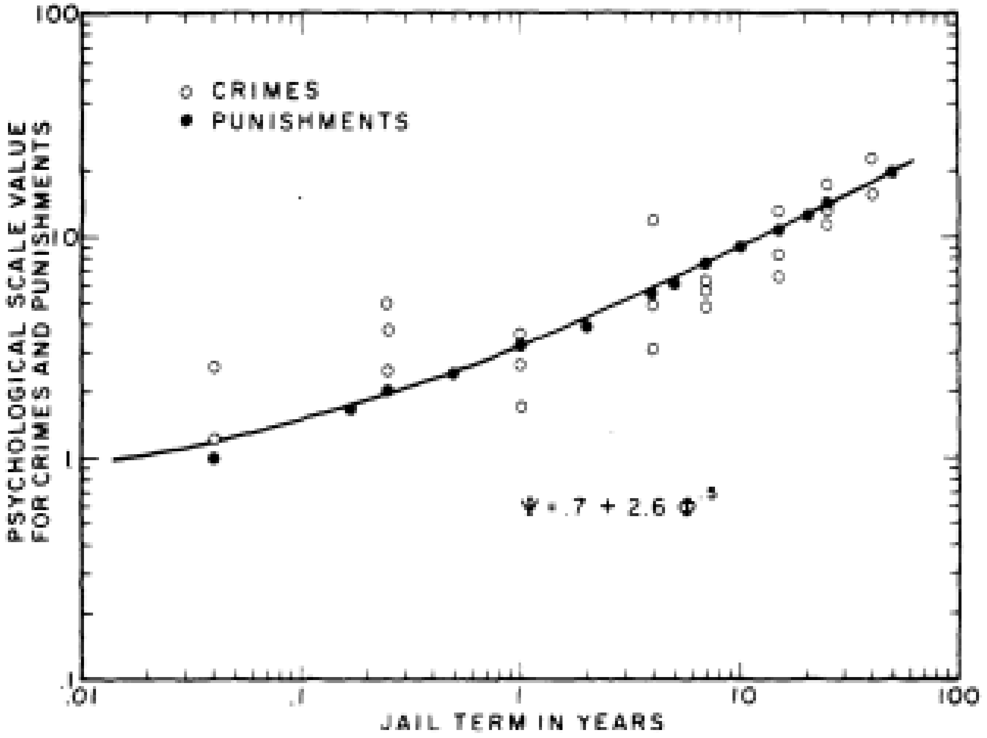
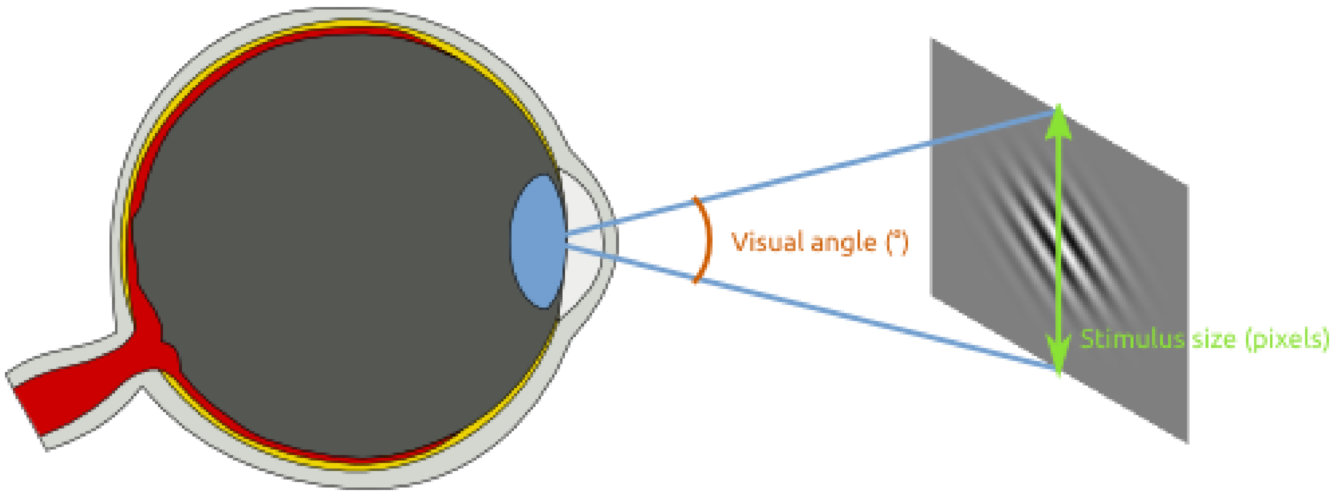


Figure 2. Geometric means of scale values of judged seriousness of crimes and judged severity of punishments as a function of jail term. By plotting the data on logarithmic coordinates, the applicability of the power law could be evaluated.

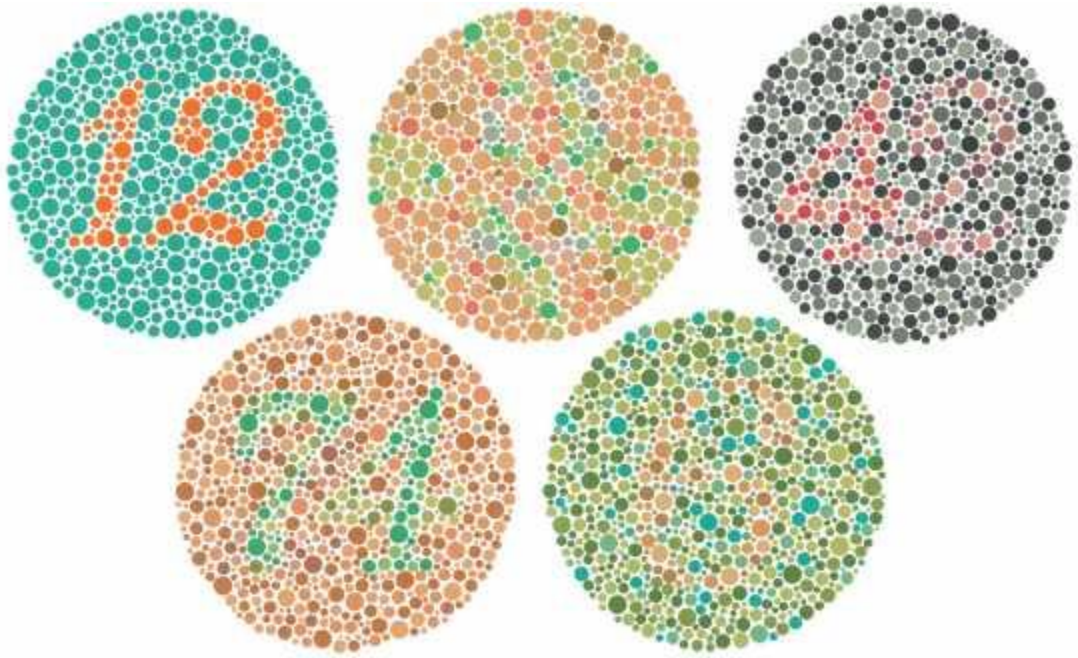
Individual participant measurements

- We are working on individual level – we need to check individual settings in order to have precisely calibrated models



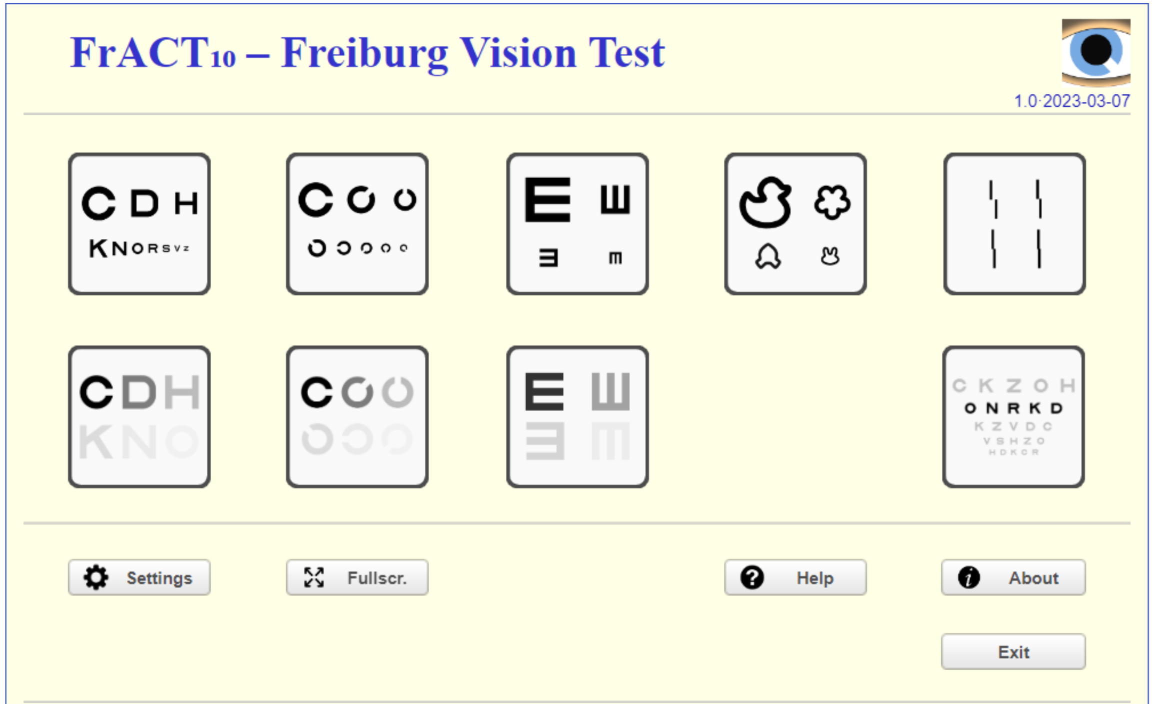
Individual participant measurements

- Isihara test



Individual participant measurements

- https://michaelbach.de/fract/



Lago, M. A. (2021). SimplePhy: An open-source tool for quick online perception experiments. *Behavior Research Methods*, 1-8.

Individual participant measurements

- https://simplephy.psych.ucsb.edu/

Behavior Research Methods (2021) 53:1669–1676
https://doi.org/10.3758/s13428-020-01515-z

SimplePhy: An open-source tool for quick online perception experiments

Miguel A. Lago [1]

Accepted: 19 November 2020 / Published online: 14 January 2021

Abstract
Because of the COVID-19 pandemic, researchers are facing unprecedented challenges that affect our ability to run in-person experiments. With mandated social distancing in a controlled laboratory environment, many researchers are searching for alternative options to conduct research, such as online experimentation. However, online experimentation comes at a cost; learning online tools for building and publishing psychophysics experiments can be complicated and time-consuming. This learning cost is unfortunate because researchers typically only need to use a small percentage of these tools' capabilities, but they still have to deal with these systems' complexities (e.g., complex graphical user interfaces or difficult programming languages). Furthermore, after the experiment is built, researchers often have to find an online platform compatible with the tool they used to program the experiment. To simplify and streamline the online process of programming and hosting an experiment, I have created SimplePhy. SimplePhy can save researchers' time and energy by allowing them to create a study in just a few clicks. All researchers have to do is select among a few experiment settings and upload the stimuli. SimplePhy is able to run most psychophysical perception experiments that require mouse clicks and button presses. In addition to collecting online behavioral data, SimplePhy can also collect information regarding the estimated viewing distance between the participant and the monitor, the screen size, and the experimental trial's timing—features not always offered in other online platforms. Overall, SimplePhy is a simple, free, open-source tool (code can be found here: https://gitlab.com/malago/simplephy) aimed to help labs conduct their experiments online.

Keywords Online · Perception · Psychophysics · Experiment · Open-source

Lago, M. A. (2021). SimplePhy: An open-source tool for quick online perception experiments. *Behavior Research Methods*, 1-8.