Cognitive (Neuro) Psychology

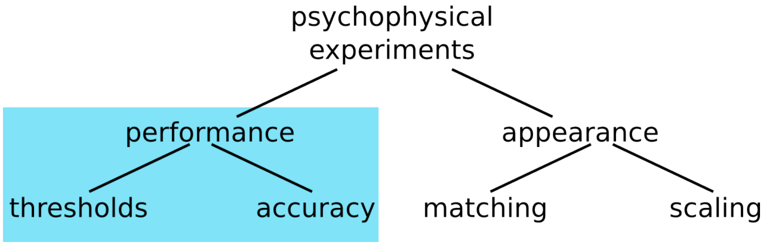
VI. Scaling Methods

Marianne Maertens

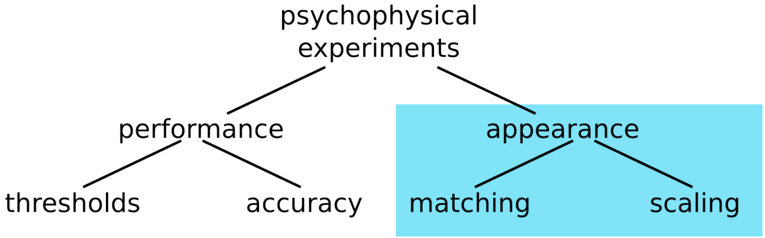
Technische Universität Berlin

July 2016

So far ...


psychophysical experiments
performance
appearance
thresholds
accuracy
matching
scaling

So far ...


psychophysical
experiments
performance
appearance
thresholds
accuracy
matching
scaling

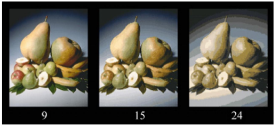
Perceptual Scales

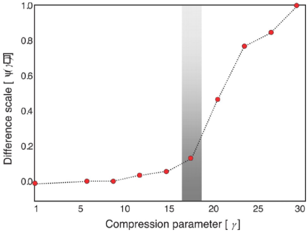
describe the relationship between the perceived and physical magnitudes of a stimulus, e.g. transparency and perceived transparency

“psychological scales”

“sensory scales”

“transducer functions”





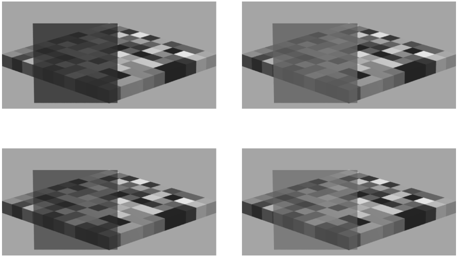
Perceptual Scales

describe the relationship between the perceived and physical magnitudes of a stimulus, e.g. transparency and perceived transparency

"psychological scales"

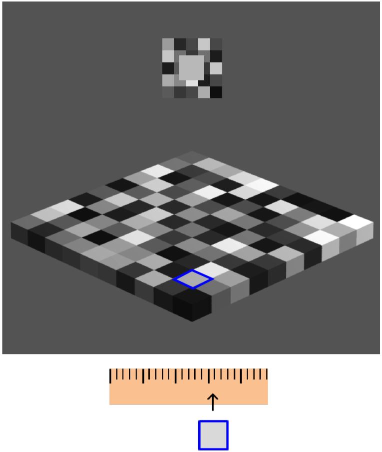
"sensory scales"

"transducer functions"



Matching vs. Scaling

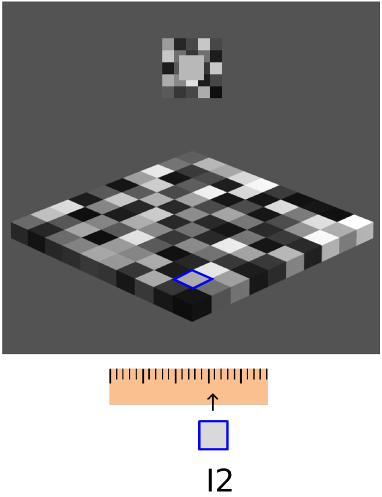
Adjust the test field so that it looks like the target



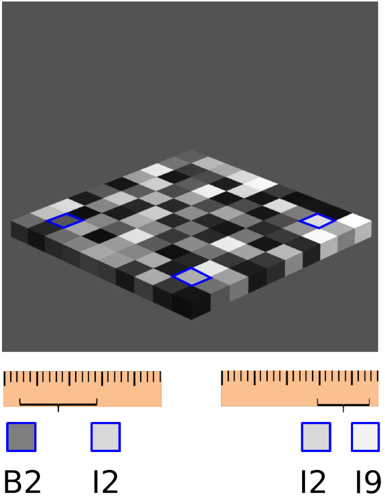
I2

Matching vs. Scaling

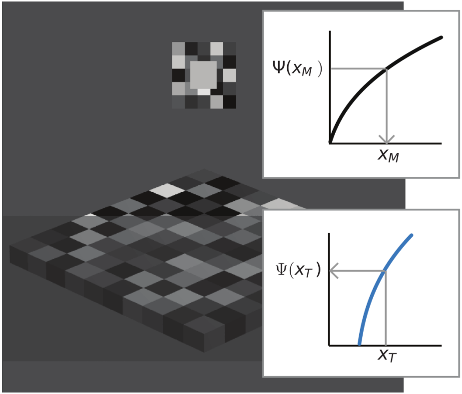
Adjust the test field so that it looks like the target

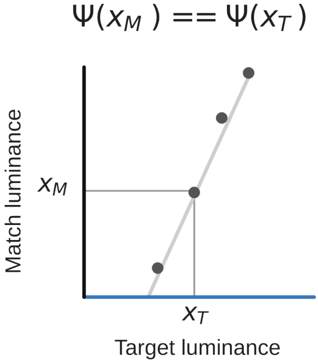


Which of the pairs looks more different

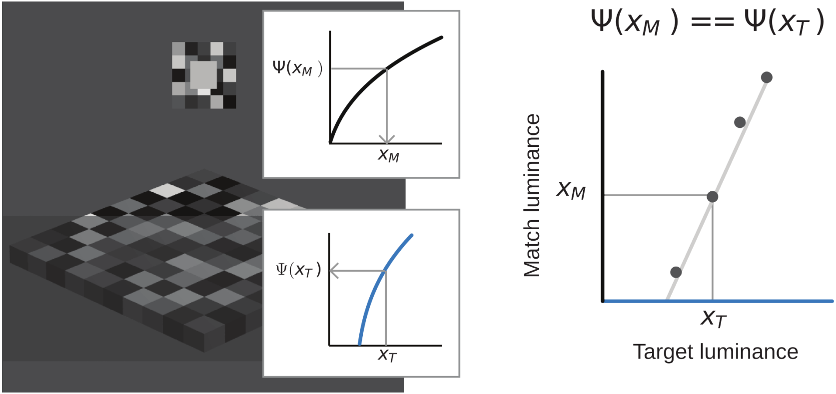


(Asymmetric) Matching



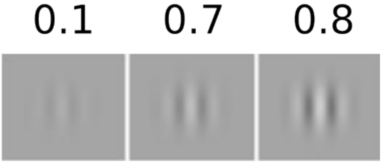


(Asymmetric) Matching



- matching measures internal variables indirectly
- it is prone to response strategies (Runeson!)

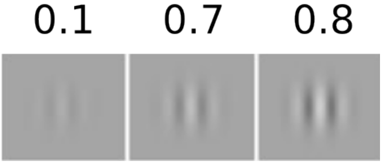
Types of perceptual scales



ordinal:

- number stimulus magnitudes according to their rank order along perceptual continuum, difference between any pair of number does not necessarily correspond to magnitude of the perceptual difference, e.g. 1, 2, 3
- differences between numbers do not correspond to perceived differences

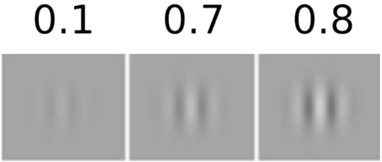
Types of perceptual scales



interval:

- differences between number correspond to perceptual differences, even though numbers themselves are arbitrary, e.g. 1, 5, 6 or 4, 12, 14, an interval scale can be transformed without loss of information by the equation $aX + b$
- does not capture perceived relative magnitudes of the stimulus dimension

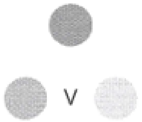
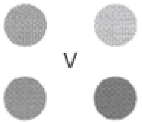
Types of perceptual scales



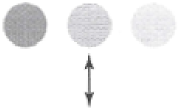
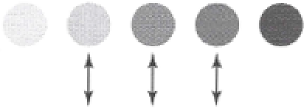
ratio:

- capture relative perceived magnitudes, e.g. values of 1 and 5 indicate that the second value is five times the first

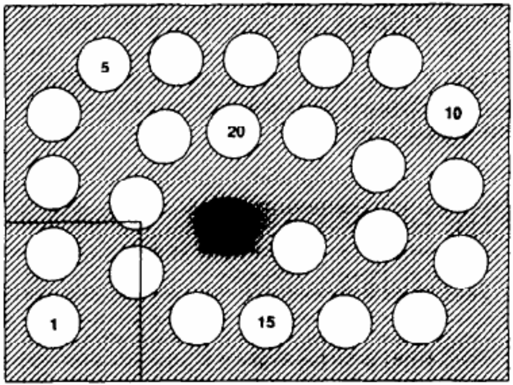
Forced-choice vs. non-forced choice scaling procedures

N	Task name	Stimuli	Task
2	Paired-comparisons		Select the brighter stimulus
3	Method of triads		Select the stimulus from the bottom pair that is most similar (or most different) to the top stimulus
4	Method of quadruples		Select the pair (top or bottom) that is more similar (or more different)

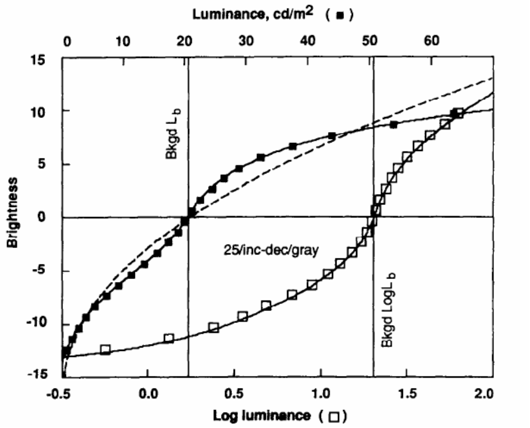
Forced-choice vs. non-forced choice scaling procedures

N	Task name	Stimuli	Task
3	Partition scaling		Adjust middle stimulus until perceptually mid-way between the anchors either side
> 3	Multi-partition scaling		Adjust stimuli between the anchors at either end until all stimuli are at equal perceptual intervals

Example: Multi-partition scaling

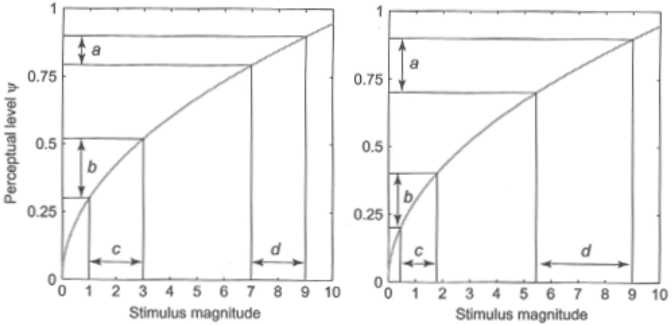


Example: Multi-partition scaling



General principle of a perceptual scale

- perceptual scale is power function $\Psi(x) = a * S^n$
- quadruples
- equal physical magnitudes, different perceptual magnitudes and vice versa



Perceptual scales and internal noise

Why not construct a perceptual scale from JNDs?

Perceptual scales and internal noise

Why not construct a perceptual scale from JNDs?

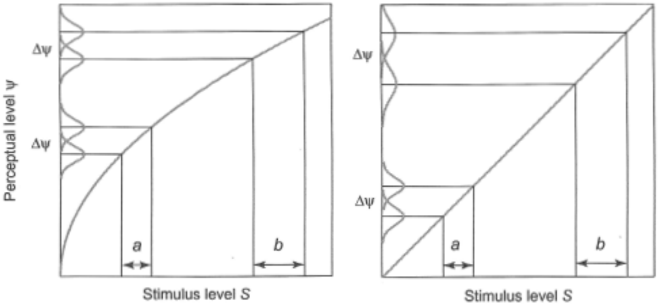
thought experiment:

- start with low stimulus level, baseline
- measure JND between baseline and a higher stimulus level
- second baseline will be first baseline plus the JND
- measure JND between second baseline and a higher stimulus
- ...
- series of baselines separated by JNDs that span the entire stimulus range

= Discrimination scale, Discrimination or Fechnerian scaling

Perceptual scales and internal noise

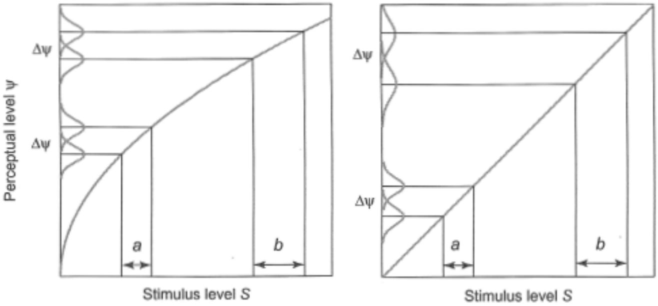
- JND for some criterion level, e.g. 75% correct, depends on signal-to-noise ratio $\frac{\Delta\psi}{\sigma}$



- *additive* noise
- *multiplicative* noise

Perceptual scales and internal noise

- JND for some criterion level, e.g. 75% correct, depends on signal-to-noise ratio $\frac{\Delta\Psi}{\sigma}$



- *additive* noise
- *multiplicative* noise

⇒ impossible to derive the shape of the underlying perceptual scale from JNDs

Maximum Likelihood Difference Scaling - MLDS

Maloney & Yang, 2003

- forced-choice scaling procedure
- state-of-the-art optimization
- produces interval perceptual scale

How MLDS works

- set of stimulus magnitudes $S_1, S_2, S_3, ..., S_n$
- $\Psi(2), \Psi(3), \Psi(4), ..., \Psi(n-1)$ are free parameters that have to be estimated, $\Psi(1)$ and $\Psi(n)$ are fixed at 0 and 1

How MLDS works

- set of stimulus magnitudes $S_1, S_2, S_3, ..., S_n$
- $\Psi(2), \Psi(3), \Psi(4), ..., \Psi(n-1)$ are free parameters that have to be estimated, $\Psi(1)$ and $\Psi(n)$ are fixed at 0 and 1

- trial 1: S_1, S_2 and S_3, S_4,
- observer: S_1, S_2 is more different
- for a given test set of $\Psi(S)$s MLDS calculates the probability that a hypothetical observer characterized by these parameters will respond that S_1, S_2 has the larger perceived difference = likelihood for this trial

How MLDS works

- set of stimulus magnitudes $S_1, S_2, S_3, ..., S_n$
- $\Psi(2), \Psi(3), \Psi(4), ..., \Psi(n-1)$ are free parameters that have to be estimated, $\Psi(1)$ and $\Psi(n)$ are fixed at 0 and 1

- trial 1: S_1, S_2 and S_3, S_4,
- observer: S_1, S_2 is more different
- for a given test set of $\Psi(S)$s MLDS calculates the probability that a hypothetical observer characterized by these parameters will respond that S_1, S_2 has the larger perceived difference = likelihood for this trial

- likelihoods of all trials are multiplied to obtain across-trials likelihood

Single trial example

- initial guesses for parameters:
  $\Psi(1) = 0.5$, $\Psi(2) = 0.7$, $\Psi(3) = 0.2$, $\Psi(4) = 0.3$
- internal decision noise is: $\sigma_d = 0.1$

$\Rightarrow$ $L(S_1, S_2)|(\Psi(1), \Psi(2), \Psi(3), \Psi(4))$

Single trial example

- initial guesses for parameters:
  $\Psi(1) = 0.5$, $\Psi(2) = 0.7$, $\Psi(3) = 0.2$, $\Psi(4) = 0.3$
- internal decision noise is: $\sigma_d = 0.1$

$\Rightarrow \; L(S_1, S_2)|(\Psi(1), \Psi(2), \Psi(3), \Psi(4))$

$$D = |\Psi(2) - \Psi(1)| - |\Psi(4) - \Psi(3)| = |(0.7 - 0.5)| - |0.3 - 0.2| = 0.1$$

Single trial example

- initial guesses for parameters:
  $\Psi(1) = 0.5$, $\Psi(2) = 0.7$, $\Psi(3) = 0.2$, $\Psi(4) = 0.3$
- internal decision noise is: $\sigma_d = 0.1$

$\Rightarrow$ $L(S_1, S_2)|(\Psi(1), \Psi(2), \Psi(3), \Psi(4))$

$$D = |\Psi(2) - \Psi(1)| - |\Psi(4) - \Psi(3)| = |(0.7 - 0.5)| - |0.3 - 0.2| = 0.1$$

- convert to z-score $\frac{D}{\sigma_d} = 1$
- calculate area under the standard normal distribution
  $\Phi(z = 1) = 0.8413$

Single trial example

- initial guesses for parameters:
  $\Psi(1) = 0.5$, $\Psi(2) = 0.7$, $\Psi(3) = 0.2$, $\Psi(4) = 0.3$
- internal decision noise is: $\sigma_d = 0.1$

$$\Rightarrow \; L(S_1, S_2) | (\Psi(1), \Psi(2), \Psi(3), \Psi(4))$$

$$D = |\Psi(2) - \Psi(1)| - |\Psi(4) - \Psi(3)| = |(0.7 - 0.5)| - |0.3 - 0.2| = 0.1$$

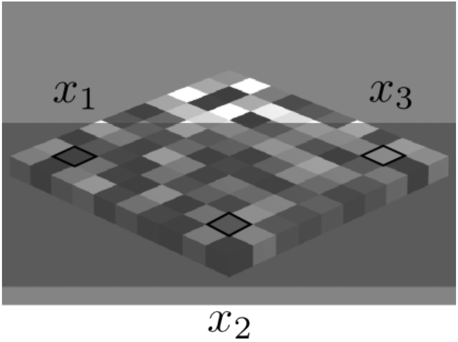
- convert to z-score $\frac{D}{\sigma_d} = 1$
- calculate area under the standard normal distribution
  $\Phi(z = 1) = 0.8413$

$$\Rightarrow \; L(S_3, S_4) | (\Psi(1), \Psi(2), \Psi(3), \Psi(4)) = (1 - 0.8413)$$

Across-trials likelihood

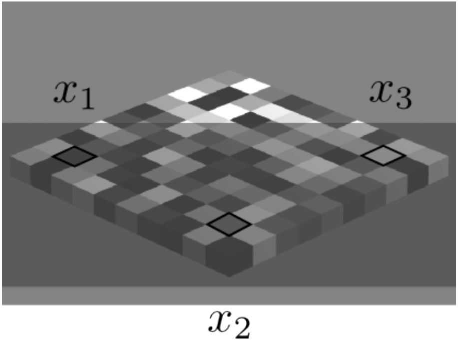
1. calculate likelihoods for all trials
2. multiply individual likelihoods across trials
3. compute logarithm of the result
4. repeat procedure for other set of $\Phi(S)$ and σ_d
5. select the set that gives the largest across-trials likelihood

MLDS at work - constructing a lightness scale



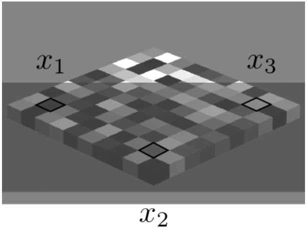
"Which pair looks more different, (x_1, x_2) *or* (x_2, x_3)*?"*

MLDS at work - constructing a lightness scale

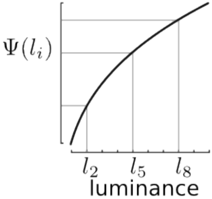


Decision model: $\Delta = (\Psi(x_3) - \Psi(x_2)) - (\Psi(x_2) - \Psi(x_1)) + \epsilon,$
$\epsilon \sim N(0, \sigma^2)$

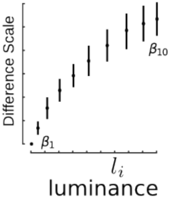
MLDS at work - constructing a lightness scale



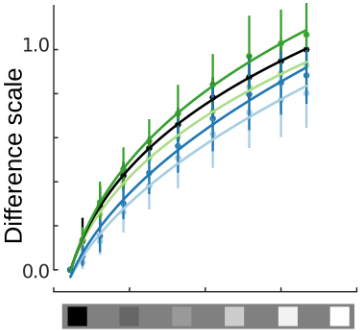
$$g(E[Y]) = X * \beta$$



$$\begin{bmatrix}0\\0\\1\\0\\ \\ \vdots\end{bmatrix} \quad \begin{bmatrix}0&1&0&0&-2&0&0&1&0&0\\0&0&1&0&0&0&0&-2&1&0\\0&1&0&0&-2&0&0&1&0&0\\1&0&-2&0&0&0&0&0&1&0\\1&0&0&0&0&-2&0&0&0&1\\ &&&&\vdots&&&&&\end{bmatrix} \quad \begin{bmatrix}\beta_1\\\beta_2\\\beta_3\\\beta_4\\\beta_5\\\beta_6\\\beta_7\\\beta_8\\\beta_9\\\beta_{10}\end{bmatrix}$$



MLDS at work - constructing a lightness scale



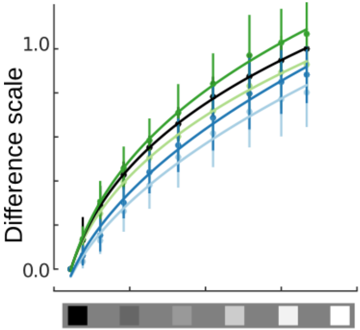
- human observers are more sensitive to differences in low intensities

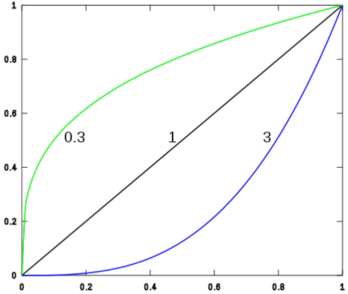
Relevance: electronic displays

Gamma correction is the name of a nonlinear operation used to encode luminance values in image systems. Gamma correction is defined by the following power-law expression:

$$V_{out} = V_{in}^{\gamma}$$

Mac 2.1, Windows 2.2



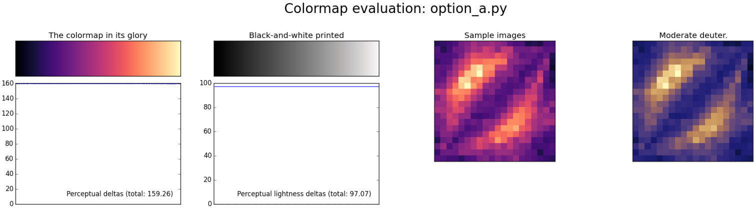


Applications

- Standardized color palettes
  e.g. Munsell
- Monitor calibration

Applications

- Standardized color palettes
  e.g. Munsell
- Monitor calibration
- Colormaps in plotting software



Summary

- forced-choice scaling: paired, triad, quadruple comparison
- non-forced-choice scaling: partition, multi-partition scaling

- discrimination (Fechnerian) scaling is appropriate when the scale is used to *predict* JNDs
- to use a JND based scale to identify the true underlying perceptual scale, internal noise must be additive

- MLDS is relevant for a variety of applications

References

- Kingdom, F.A.A. & Prins, N. (2010). Psychophysics. A practical introduction. London, UK: Elsevier Academic Press.