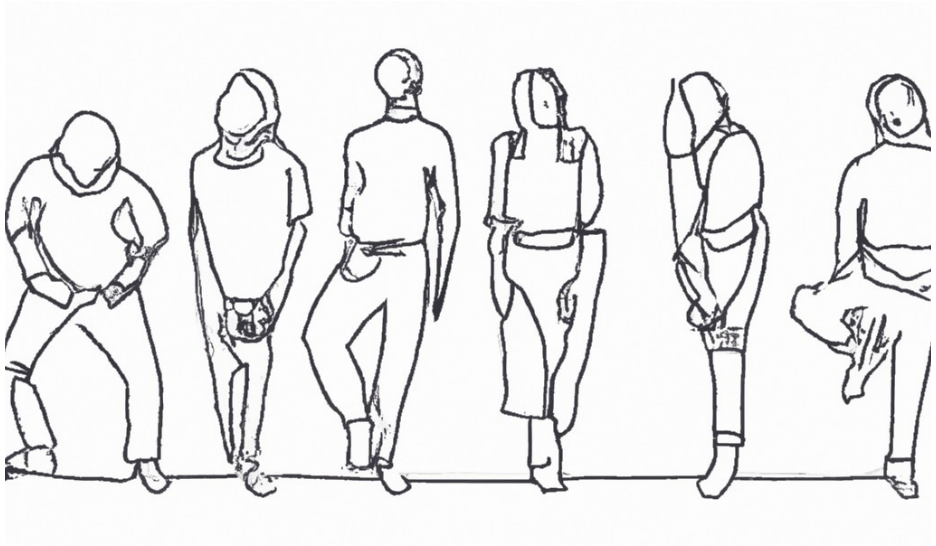
PS5210
Applied Neuroscience Methods

Workshop: analysis of behaviour



Analysis of behaviour

1. Participants perform a task, and we record their responses (multiple repetition since behaviour is variable)
2. <u>We calculate summary measures of individual performance</u>
3. We do statistical test to estimate effects and make inferences on population

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- Sometimes summary measures can be just averages (e.g., mean response time), but that is not always appropriate
- In many cases is useful to examine behaviour through the lens of a *mathematical model*

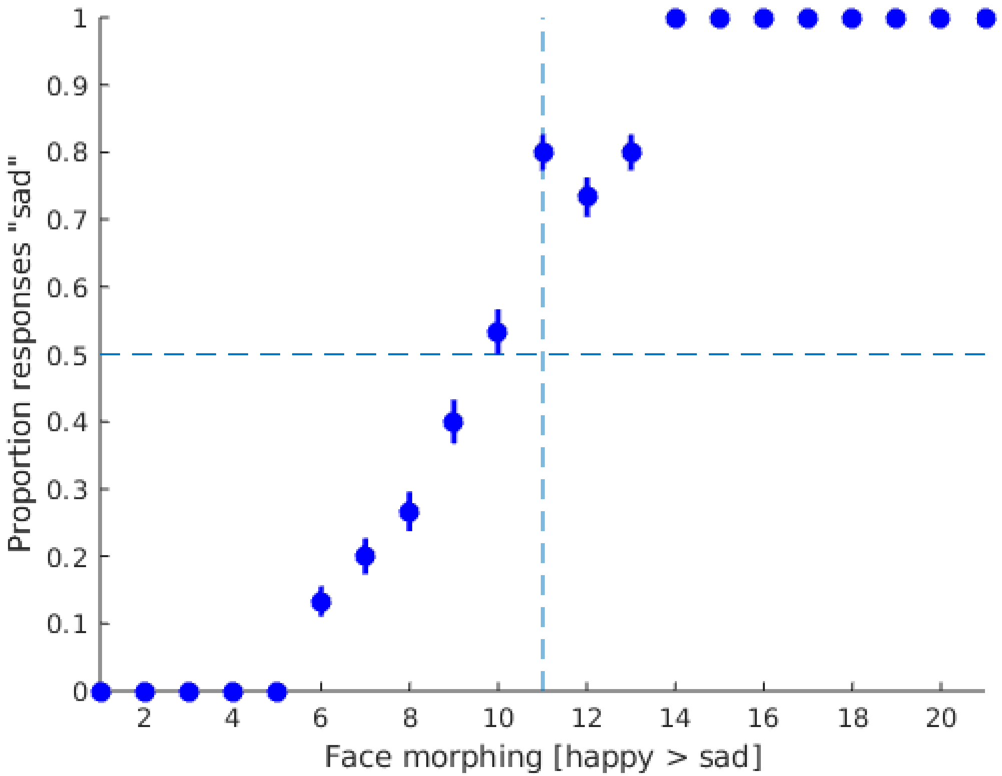
Example: emotion recognition task

- Participants are shown an image out of morphed continuum and indicate whether it is happy/sad

https://github.com/mattelisi/NeuroMethods/tree/master/experimental_tasks/emotion-recognition

Example: emotion recognition task

- Example of data



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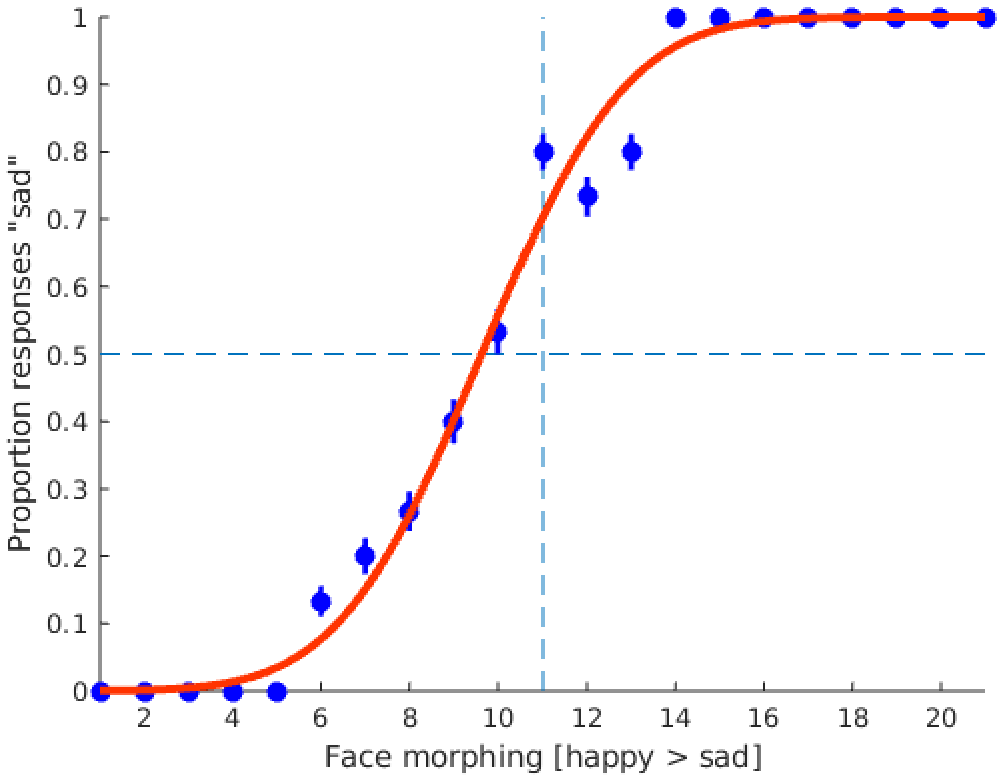

Psychometric function

(cumulative of a Gaussian probability density function)

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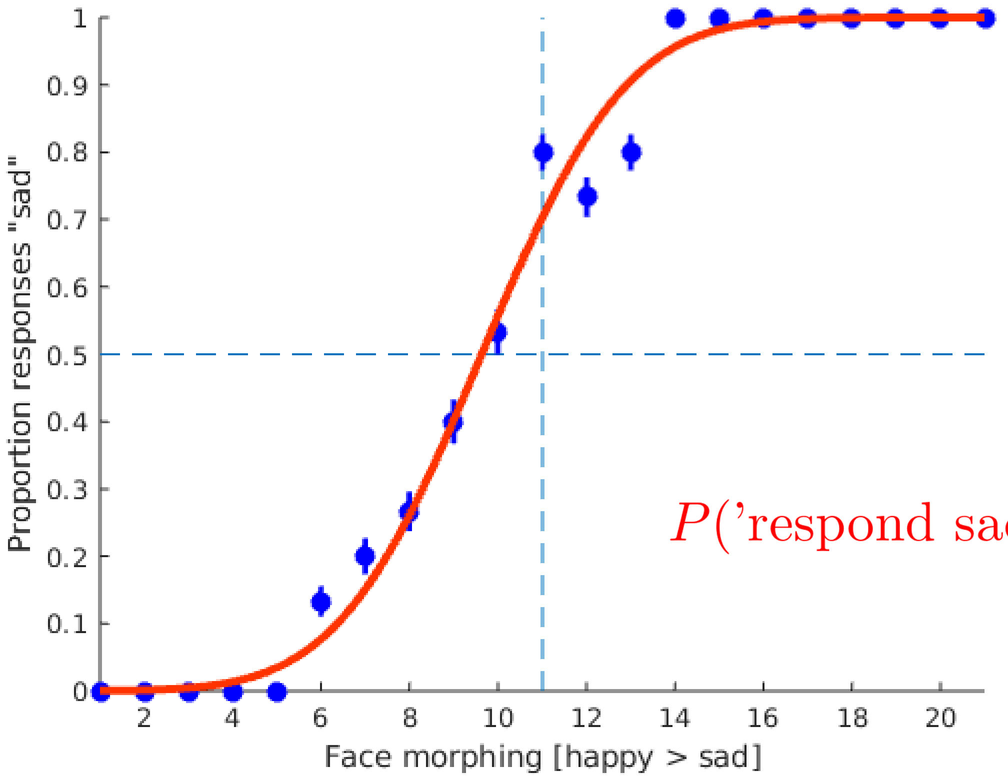

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(cumulative of a Gaussian probability density function)

$$P(\text{'respond sad'}) = \frac{1}{2}\left(1 + \text{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right)$$

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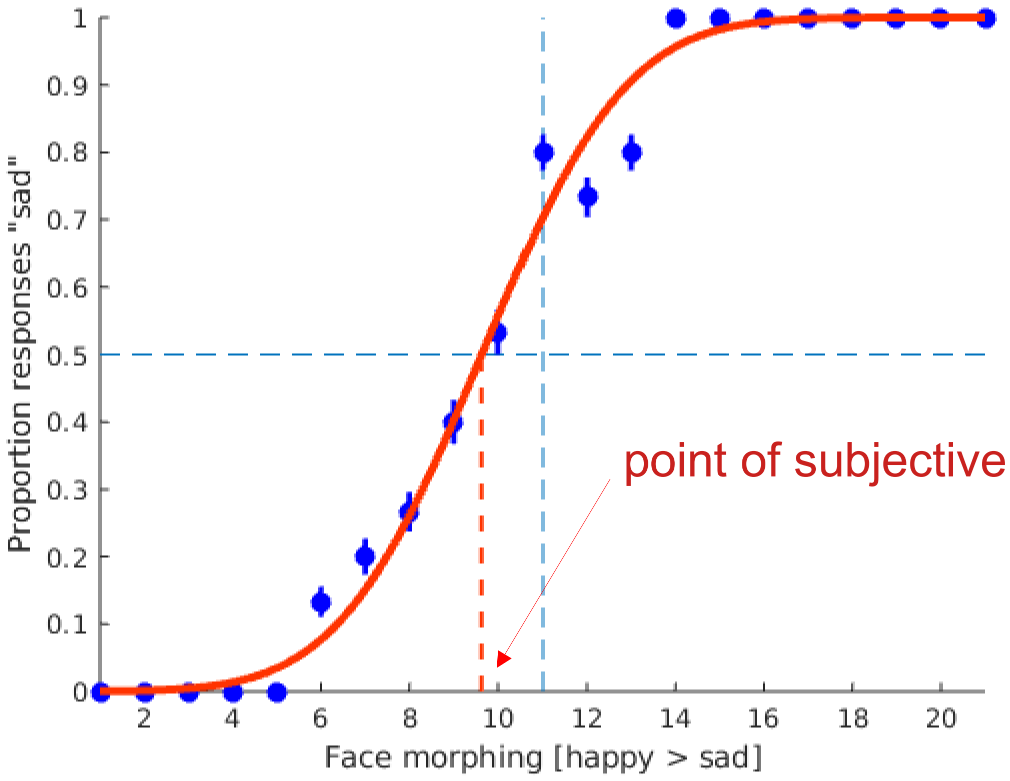

Psychometric function

(cumulative of a Gaussian probability density function)

point of subjective equality (PSE)

Maximum likelihood estimation (MLE)

- Find the parameter values that maximize the probability (likelihood) of the data (given the model)
- The probability of the data is given by

$$P(\text{'respond sad'}) = \frac{1}{2}\left(1 + \text{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right)$$

$$P(\text{'respond happy'}) = 1 - P(\text{'respond sad'})$$

Maximum likelihood estimation (MLE)

- The probability of the data as a whole is obtained by multiplying the probability of individual responses

$$P(y_1, y_2, \ldots, y_n \mid \mu, \sigma) = P(y_1 \mid \mu, \sigma) P(y_2 \mid \mu, \sigma) \ldots P(y_n \mid \mu, \sigma)$$

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- In practice, we usually take the logarithm of the likelihood, because it transform the product into a sum; we call this the *log-likelihood function*

$$\mathcal{L}(y_1, \ldots, y_n \mid \mu, \sigma) = \log(P(y_1 \mid \mu, \sigma)) + \ldots + \log(P(y_n \mid \mu, \sigma))$$

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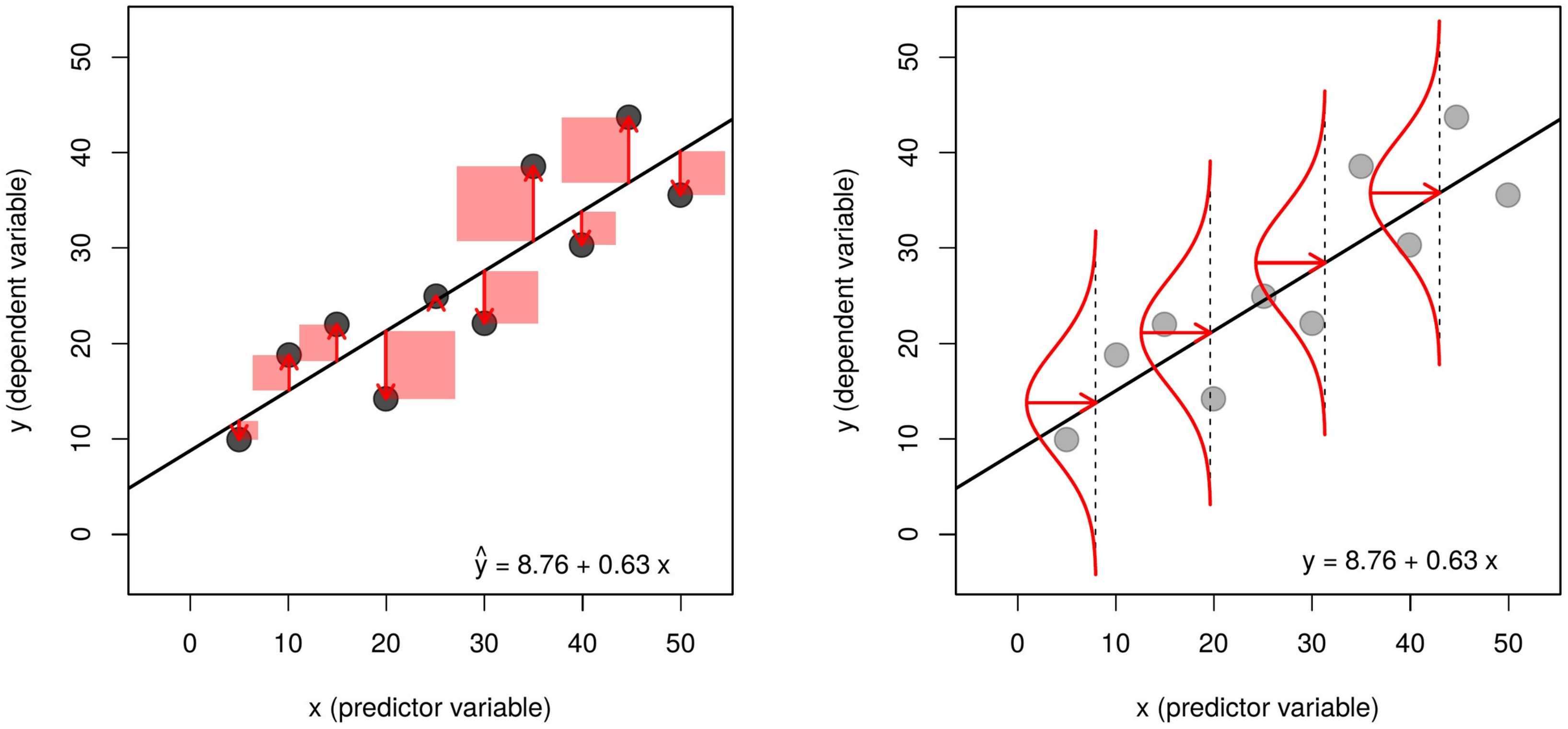
- In general, we often use *numerical optimization algorithms* that iteratively test different values of the parameters and find the maximum using a trial-and -error procedure (sort of); for example see function `fminsearch()` in Matlab, or function `optim()` in R
- The approach is general and can be used to fit *any* model
(as long as you can write and compute the likelihood function)

Maximum likelihood estimation (MLE)

- Least square estimation, used in linear regression, is a special case of MLE in which the probability of the data is given by a Gaussian distribution



- Psychometric function augmented with a parameter λ that represents the probability of a random response (e.g. a lapse of attention)

$$P(\text{'respond sad'}) = \frac{1}{2}\lambda + (1-\lambda)\left[\frac{1}{2}\left(1+\mathrm{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right)\right]$$