Overview of Experiment Techniques and Statistical Methods

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03/05/21 lab meeting

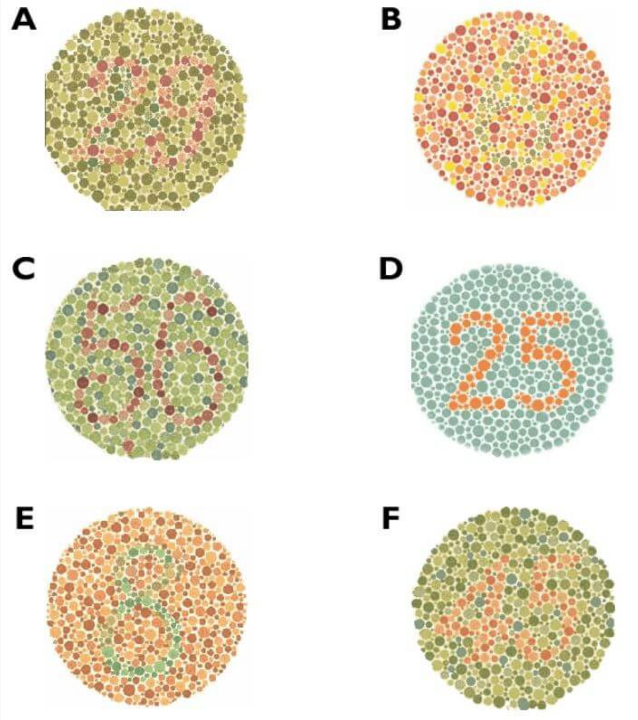
Sensorimotor & Robotics Lab

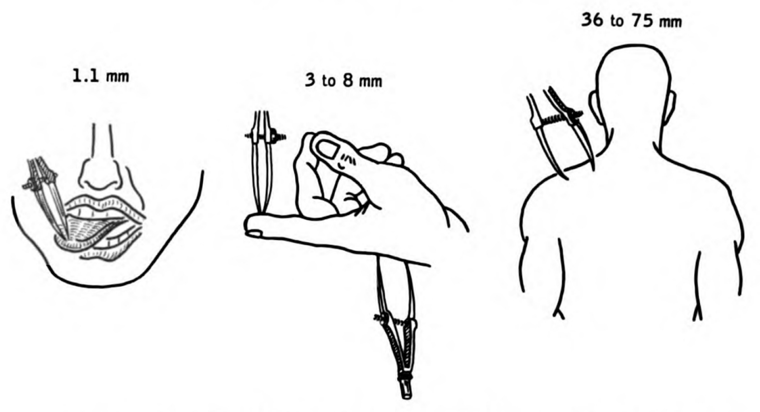
Goal

- Provide background on experimental methods most used in our lab and in the field of perceptual studies
- Introduce the concepts behind the statistical analyses used in our lab

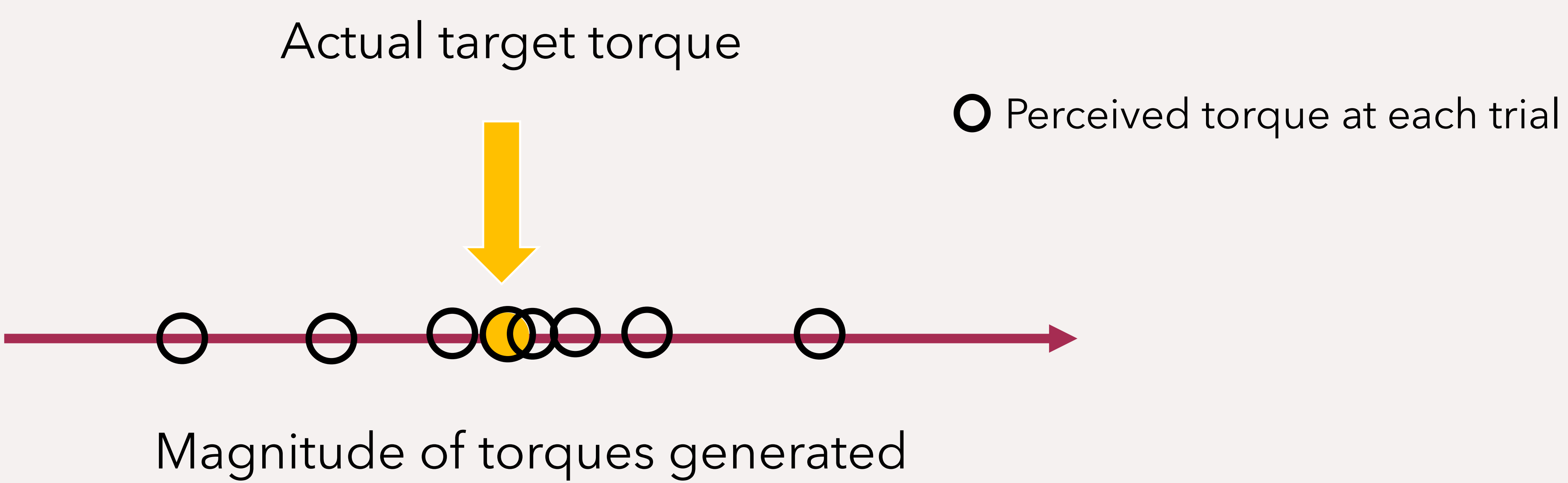
Psychophysics

"… quantitatively investigates the relationship between physical stimuli and the sensations and perceptions they affect. " (*Wikipedia* definition)

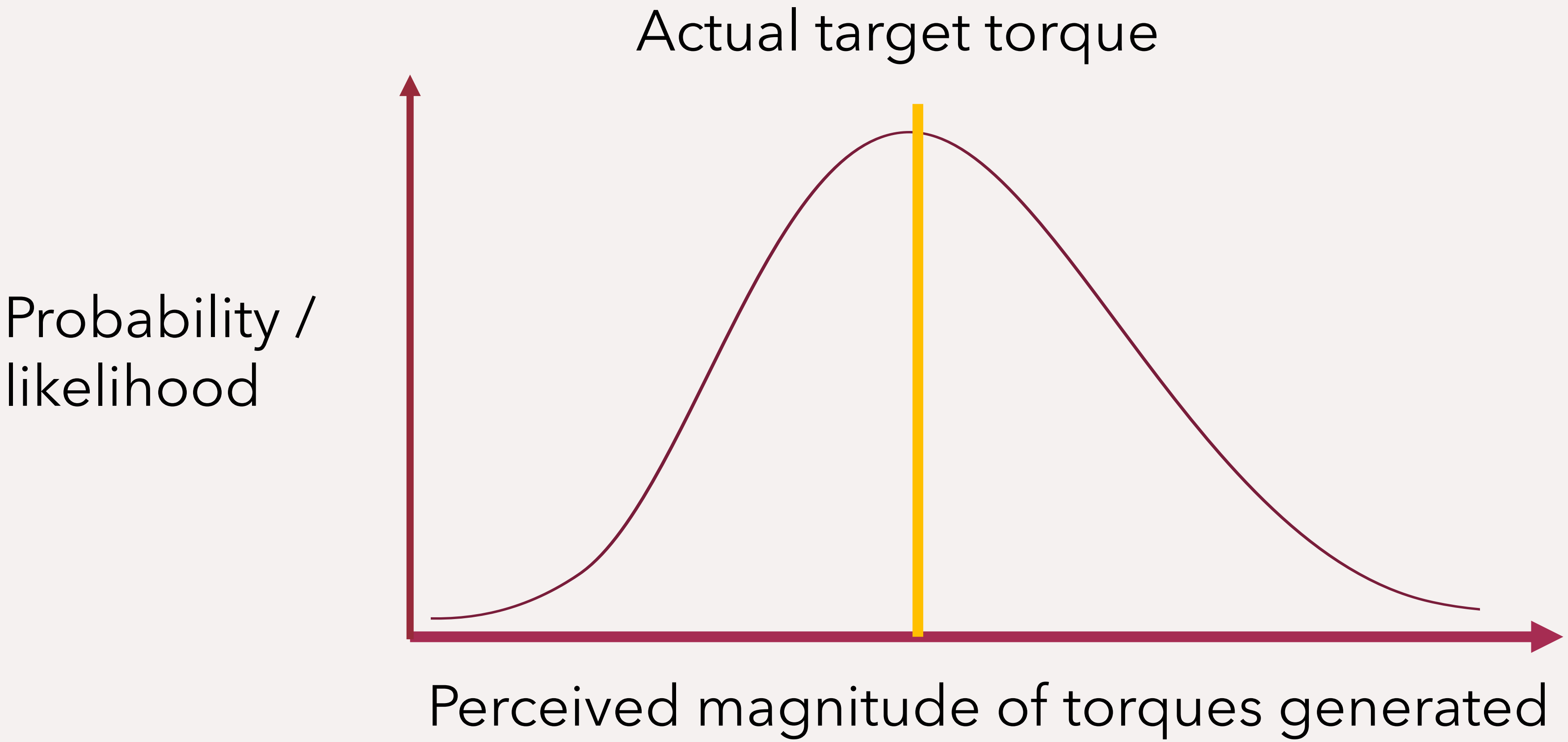




Psychophysics



Psychophysics



Classification of Psychophysical Procedures

Performance-based

- measures aptitude
- 'how good one is'

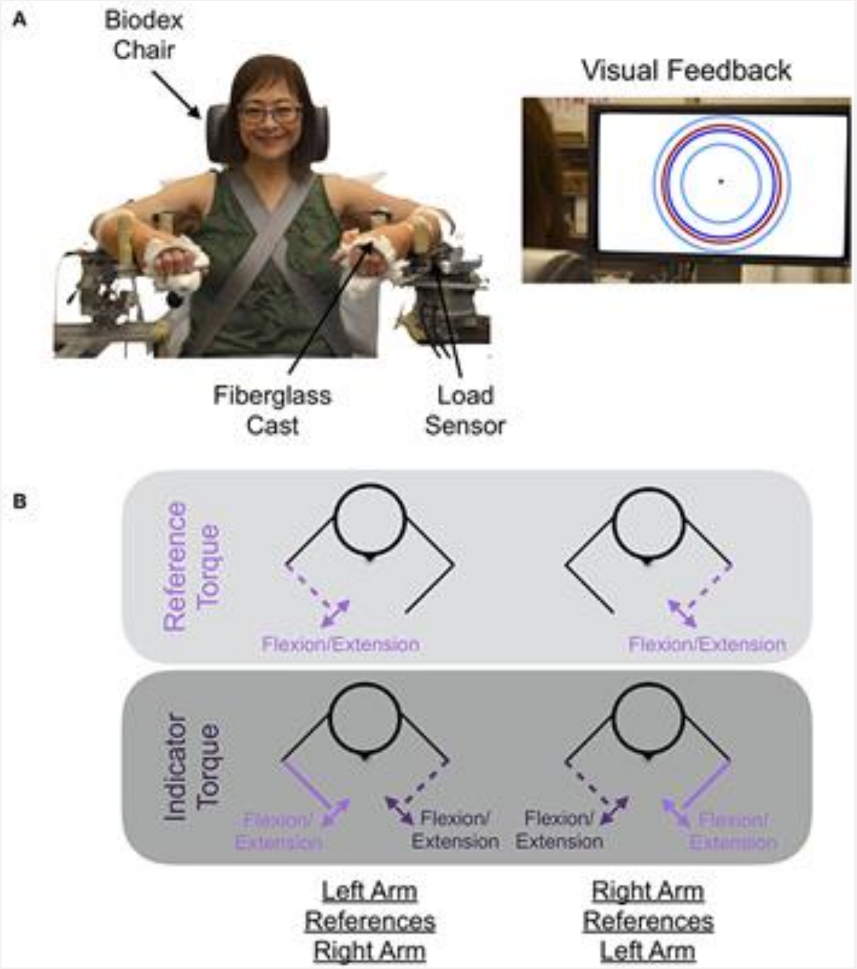
Appearance-based

- measures apparent magnitude of a stimulus
- can never be correct or incorrect

Appearance-based Method

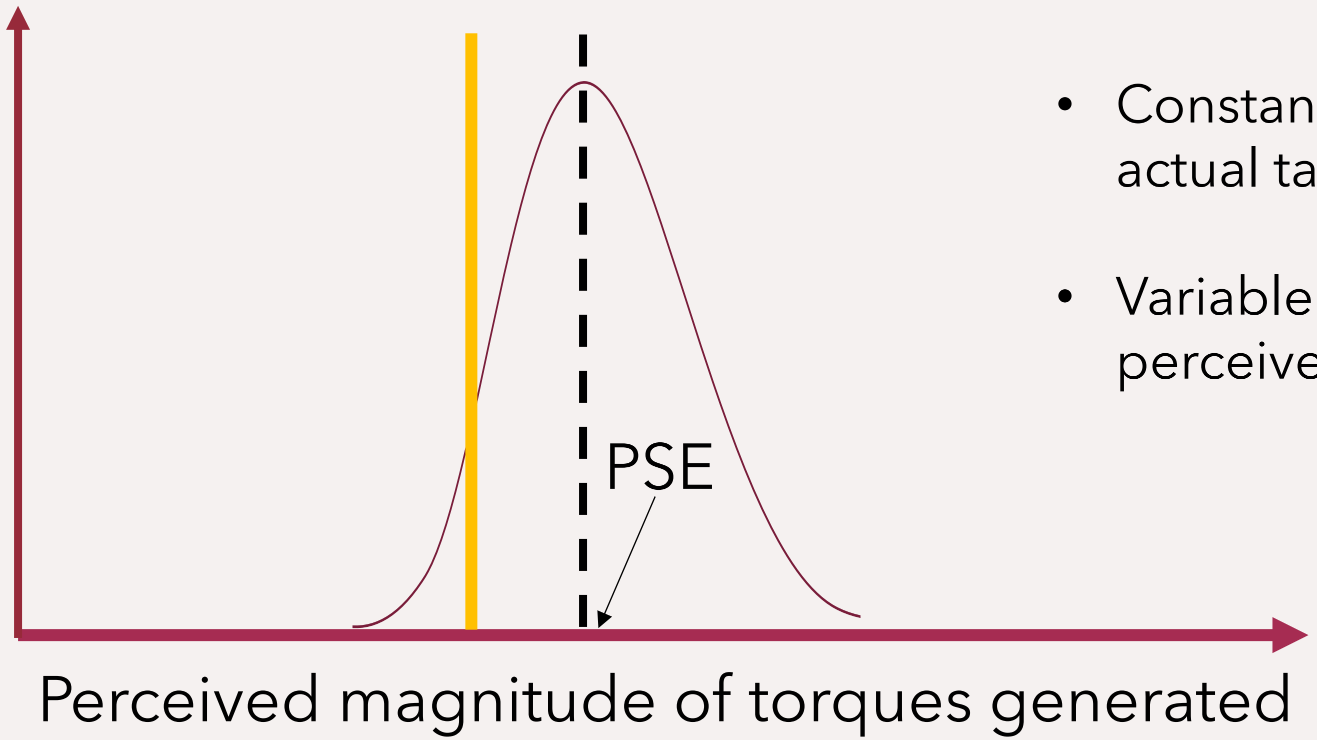
Matching task

- Point of subjective equality (PSE)
- No right or wrong answer



Appearance-based Method

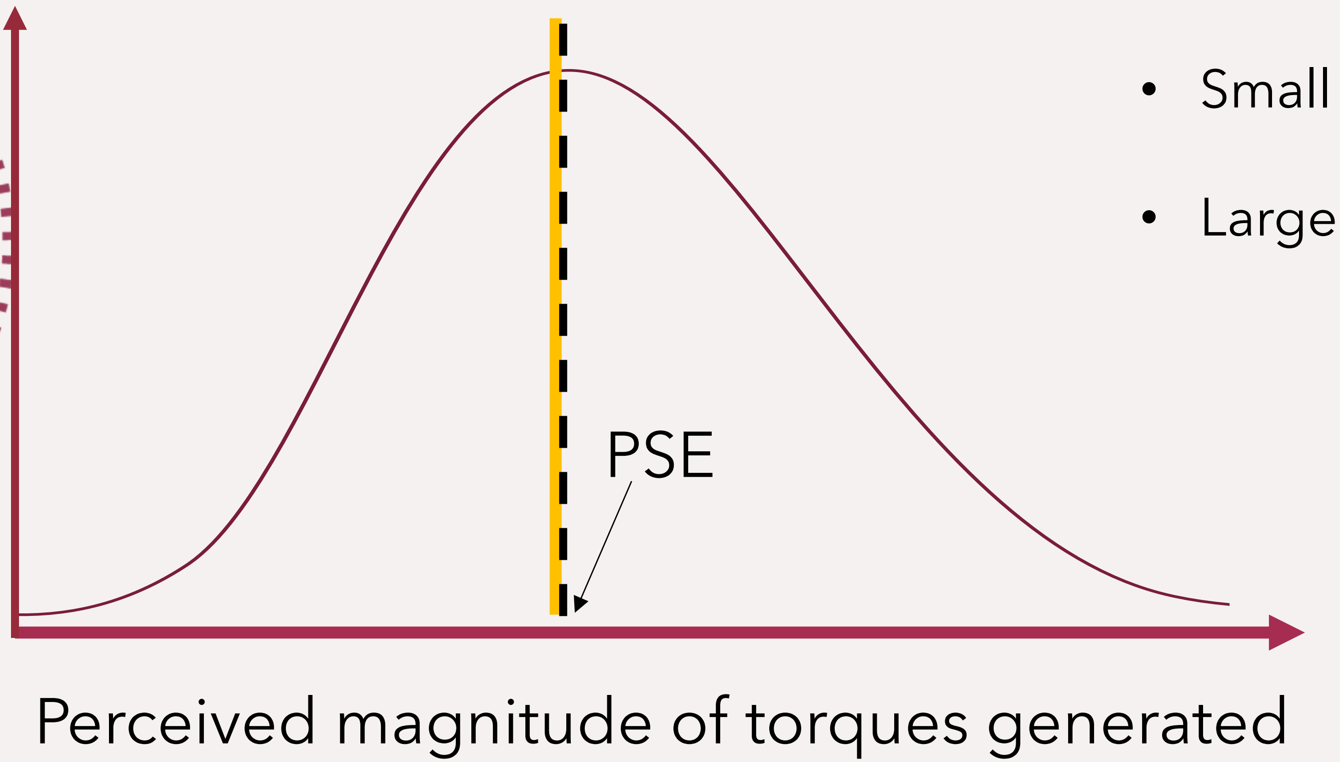
Point of Subjective Equality



- Constant error (CE): difference between actual target and the PSE
- Variable error (VE): variability of the perceived torques

Appearance-based Method

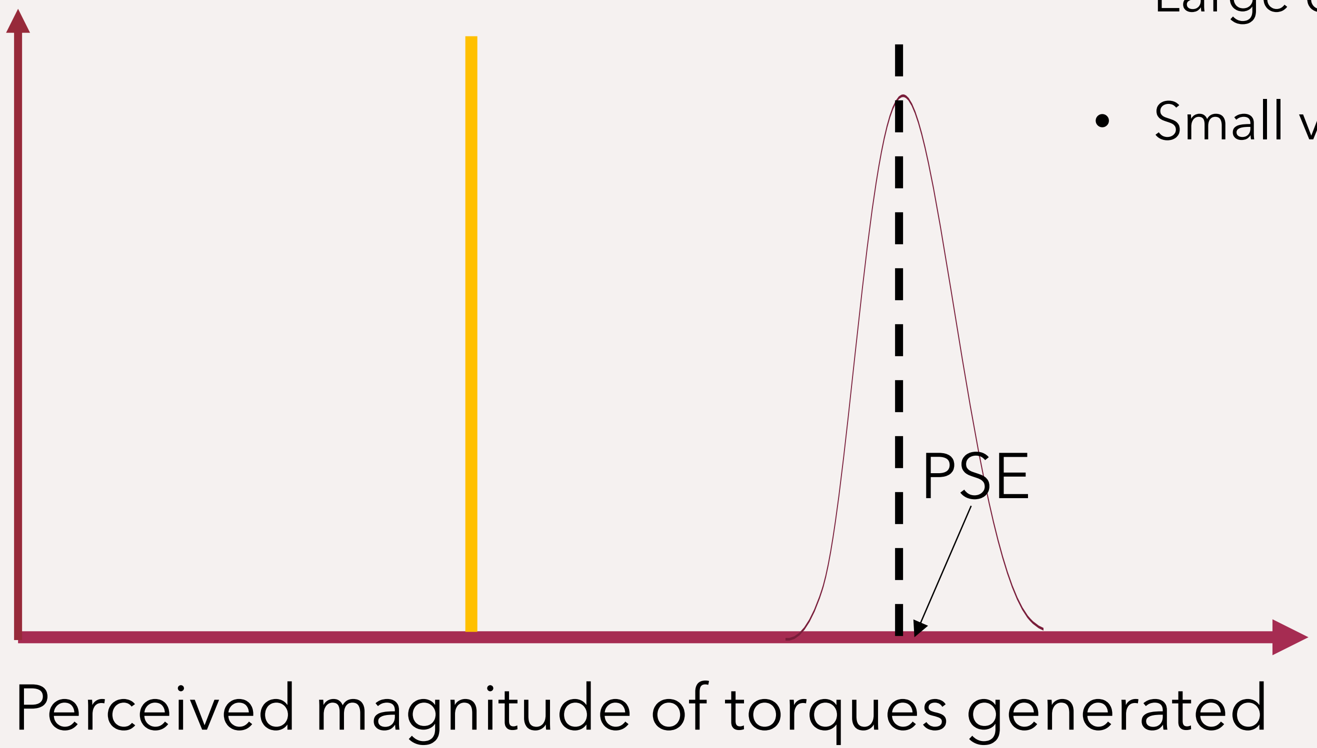
Point of Subjective Equality



- Small constant error (CE) – high accuracy
- Large variable error (VE) – low precision

Appearance-based Method

Point of Subjective Equality



- Large constant error (CE) – low accuracy
- Small variable error (VE) – high precision

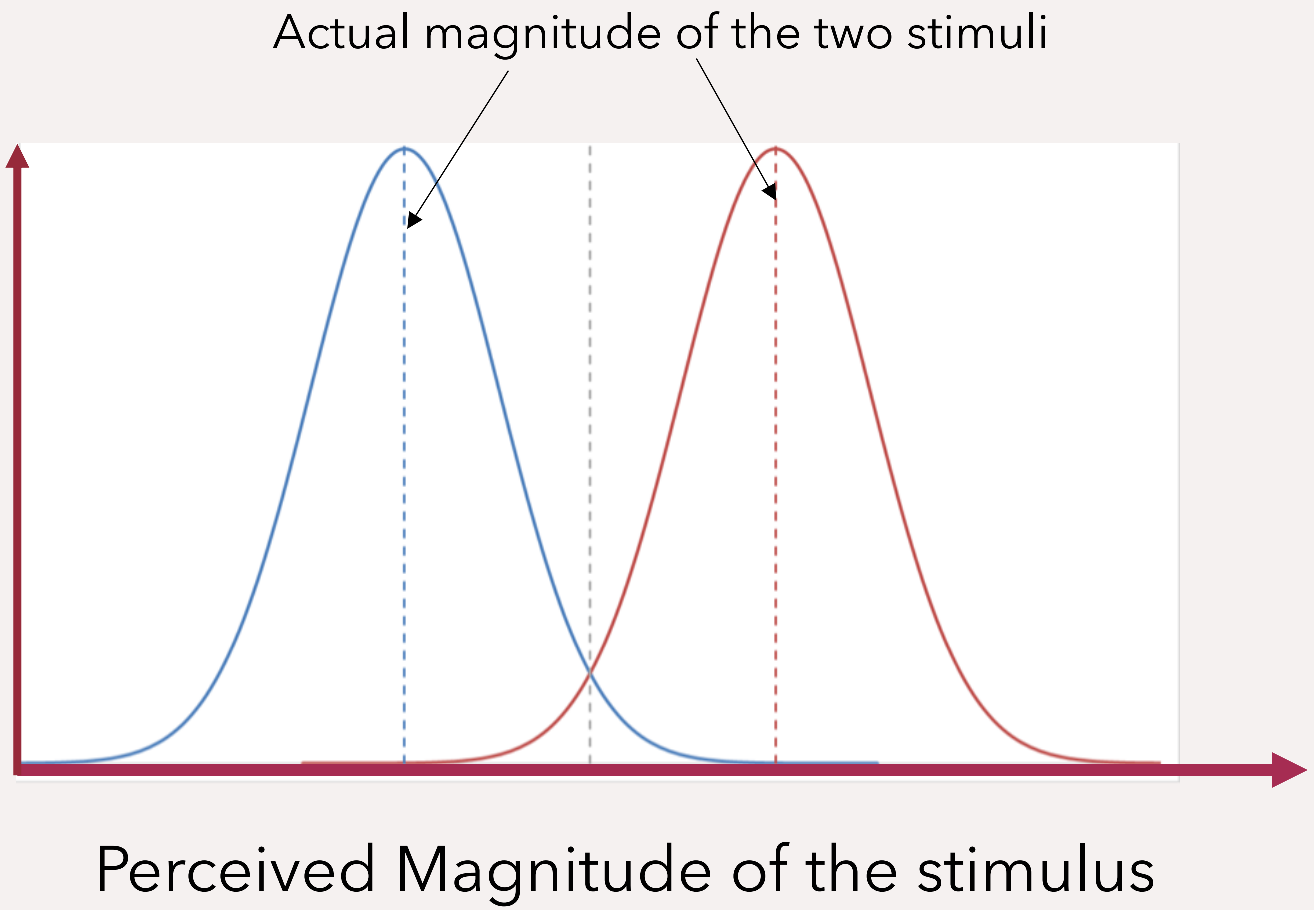
Performance-based methods

Threshold tasks

- Absolute threshold
  - Compare with null state, i.e. no stimulus
  - Detection threshold
- Relative threshold
  - Threshold of detecting change
  - Just noticeable difference

Performance-based methods

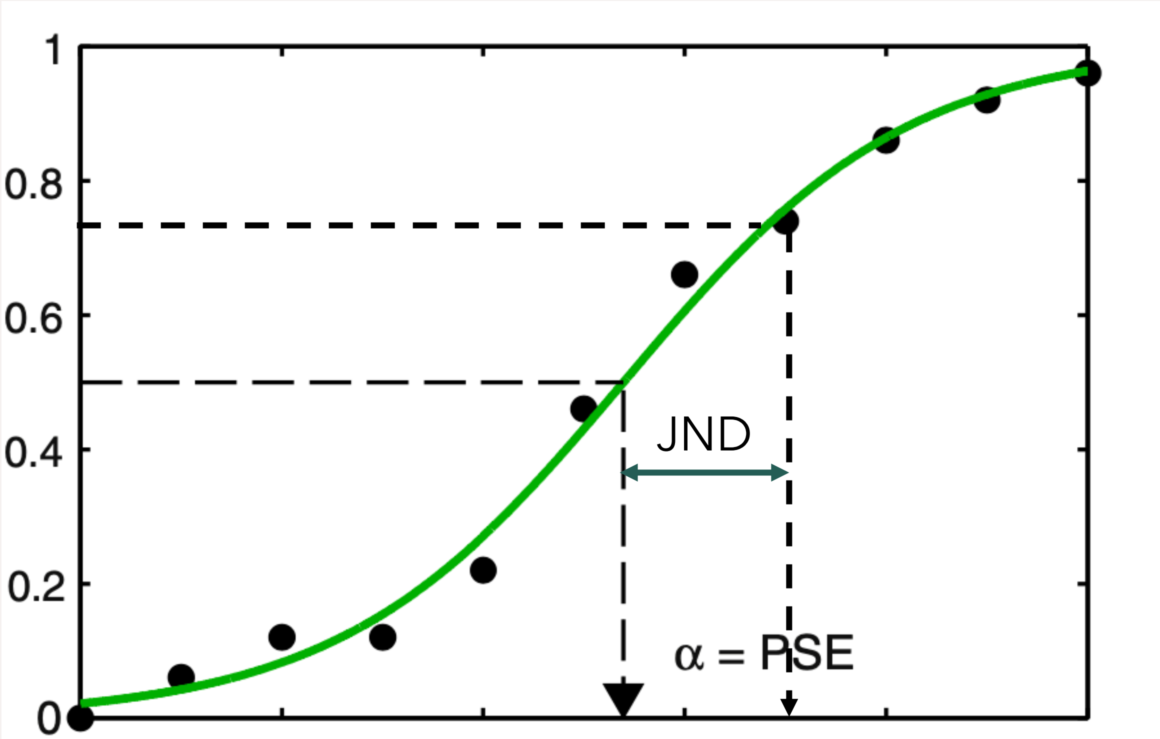
Difference threshold



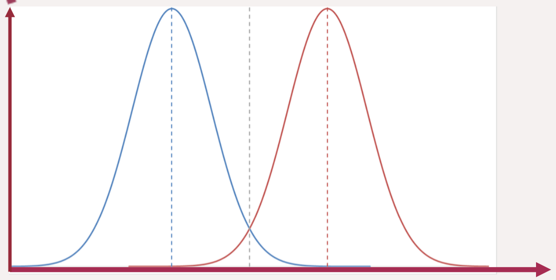
Performance-based methods

Psychometric curve

Proportion of times that blue stimulus is perceived as greater



Magnitude of the blue stimulus



Perceived Magnitude of the stimulus

Statistical Methods:
Linear mixed-effects model

Linear model

- $y = mx + b$
- Y: response variable; X: explanatory variable
- Response variable (Y) is modeled as a linear function of explanatory variables (X $\{x_1, x_2, \ldots, x_n\}$)
- X can be continuous or categorical

Linear mixed-effects model

For my study:

- Torque perceptual accuracy → measured by constant error (CE)
  - Response variable (Y)

- Effect of shoulder load on perceptual accuracy
  - Shoulder load: x_1
- Effect of stroke on perceptual accuracy
  - Control vs. stroke: x_2
- Effect of arm tested on perceptual accuracy
  - Dominant vs. non-dominant; paretic vs. non-paretic: x_3

Fixed Effects

$$Y = a(x_1) + b(x_2) + c(x_3) + \text{error}$$

Linear mixed-effects model

How to account for factors that are inherently random?

- E.g. participants

Random Effects

Parameters that are themselves random variables

Linear mixed-effects model

Linear model

- With parameters that are random at one level
- With parameters that are fixed at a higher level

Linear mixed-effects model

What would the model look like after adding in random effects?

Variation introduced
by the random effects

$$\boxed{Y} = \boxed{\beta\ X} + \boxed{\gamma} + \boxed{\varepsilon}$$

Response
variable

X: explanatory variables
β: coefficients for fixed effects

Error term

check out this blogpost by UCLA statistical consulting center

$$\overbrace{\mathbf{y}}^{\text{N x 1}} = \overbrace{\underbrace{\mathbf{X}}_{\text{N x p}} \underbrace{\boldsymbol{\beta}}_{\text{p x 1}}}^{\text{N x 1}} + \overbrace{\underbrace{\mathbf{Z}}_{\text{N x qJ}} \underbrace{\boldsymbol{u}}_{\text{qJ x 1}}}^{\text{N x 1}} + \overbrace{\boldsymbol{\varepsilon}}^{\text{N x 1}}$$

Constructing LME in R

Library nlme

```
> fit <- lme(CE ~ task, random=~1|participant, data=dataframe)
```

```
Linear mixed-effects model fit by REML
 Data: dataframe
      AIC      BIC    logLik
  316.901 328.945 -152.4505

Random effects:
 Formula: ~1 | participant
        (Intercept) Residual
StdDev:    2.405975 2.985985

Fixed effects: CE ~ task
                   Value Std.Error DF   t-value p-value
(Intercept)     2.694573  0.990112 41  2.721483  0.0095
Task1           4.097694  1.090328 41  3.758222  0.0005
Task2          -0.715900  1.113833 41 -0.642736  0.5240
Task3           0.306754  1.090328 41  0.281341  0.7799
 Correlation:
                (Intr)  Task1  Task2
Task1          -0.551
Task2          -0.539  0.489
Task3          -0.551  0.500  0.489

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-2.03062553 -0.58055447 -0.01510482  0.43369069  2.90292915

Number of Observations: 59
Number of Groups: 15
```

Linear mixed-effects model

Now what?

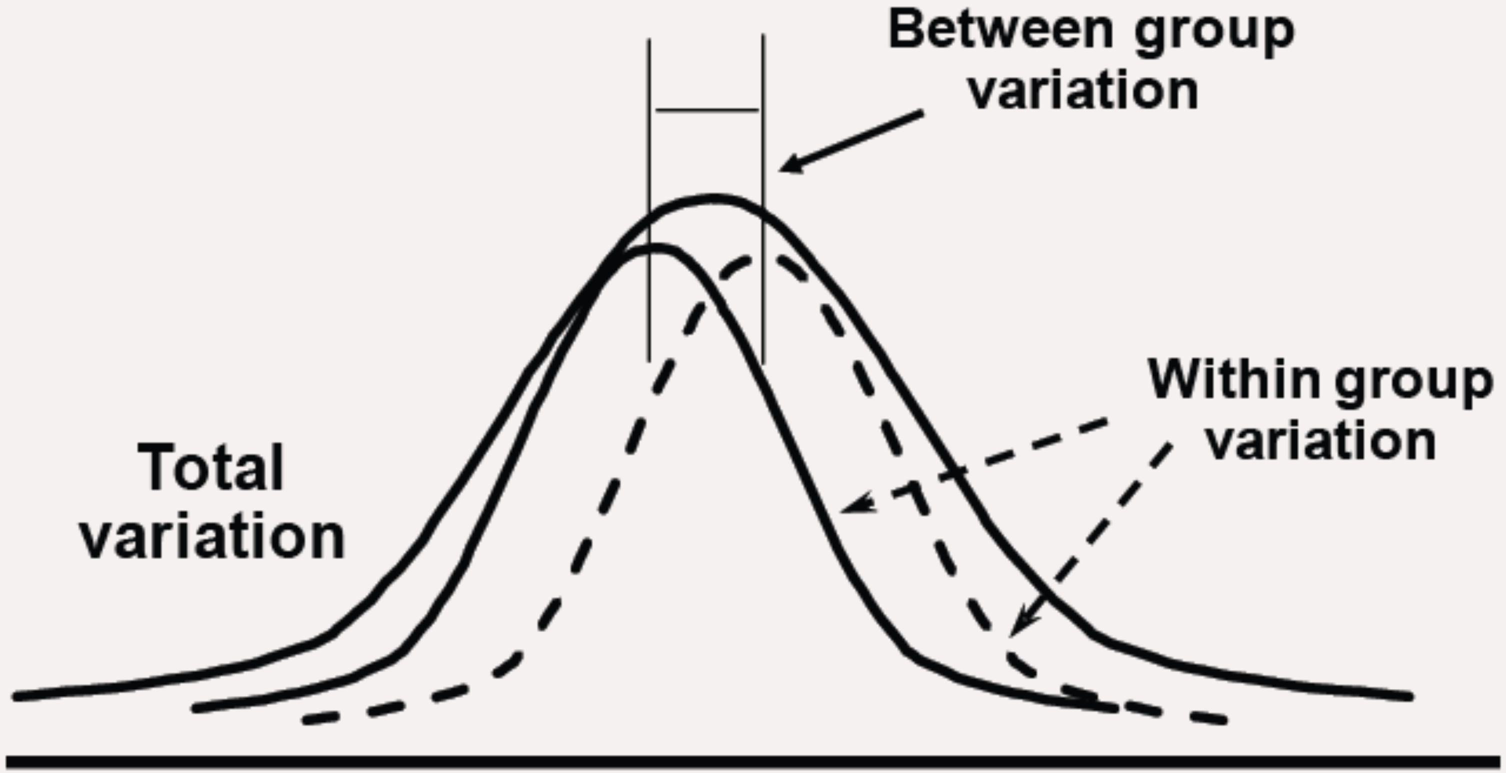
How significant are our fixed and random effects on our outcome measure (response variables)?

- Does torque-perceptual accuracy differ among tasks with different shoulder abduction load?

ANOVA on LME model

ANOVA: analysis of variance

F = (between-group variance) / (within-group variance)



ANOVA on LME model

A linear model can also obtain the results of ANOVA

Y = mX + b
Evaluate the slope (m)

Use ANOVA on constructed LME model

$$Y = \boxed{\beta} X + \boxed{\gamma} + \varepsilon$$

Advantages of LME

Assumptions for ANOVA:

- data independence,
- data normality
- equality of variances
- balance design (i.e. all groups have the same number of samples)

Linear mixed-effects model is <u>more robust</u> against these assumptions

- Can tolerate unbalanced dataset and missing values
- Takes between-subjects variability into consideration
- Better model for data with a hierarchical structure

R code for running ANOVA on LME

```
> ce_anova <- anova.lme(fit, type="marginal")
> ce_anova
            numDF denDF  F-value p-value
(Intercept)     1    41 7.406467  0.0095
task            3    41 7.725815  0.0003
```