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Correlational biases in mean response latency differences☆

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ABSTRACT

Multifarious psychological constructs are indexed by the mean latency difference (MLD), the within-subject difference between mean response latency on two tasks. Two associations consistently emerge in mean latency data. Firstly, across subjects, mean latencies on distinct tasks are positively correlated. This correlation arises from individual differences in general rates of information processing that are a shared influence on response latency in diverse tasks. Secondly, across tasks, the mean and variance of mean latency are positively correlated. Compared to a simple task, a complex task has both a larger average mean latency and a larger variance of mean latency, across subjects. Taken together, these associations make the interpretation of the MLD problematic by biasing correlations between the MLD and (a) task mean latencies, (b) the average of the mean latencies, (c) external criteria, and (d) other MLDs. A variety of mean latency transformations were evaluated and, while they differed in their effectiveness, they did not satisfactorily rectify MLD biases. An alternative approach, focusing on scale invariant contrasts of within-subject response latency distributions, is introduced in the conclusion.

With a history of over 100 years, the measure of choice reaction time maintains an important role in the modeling of mental processes. In mental chronometry, the focus of interest is often the within-individual contrast between mean response latencies on two distinct tasks. The mean latency difference (MLD) is assumed to reflect the additional processing demands in one condition, relative

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to a contrasted condition [20]. MLD scores operationalize measures in many paradigms including the Stroop task [16], semantic priming [21], task switching [17], evaluative priming [9], lexical decisions [1], and attentional networks [8].

Despite the advantageous within-individual comparison, problematic aspects of the MLD were recognized in the aging literature [24,26] where older and younger subjects are frequently compared. While older subjects exhibit larger MLDs than younger subjects, they also tend to have larger mean latencies. MLD differences between younger and older subjects may reflect actual group differences in the processing demands of the two conditions, or be an artifact of the overall slower and more variable responding of older adults, or an admixture of the two.

From a general perspective, mean response latencies are influenced by (i) subject characteristics, (ii) task demands, and (iii) the interaction of subject characteristics with task demands. In the rate amount framework [10], tasks vary in their information processing amount, individuals differ in their information processing rate, and mean response latency is the product of information amount and the reciprocal of information processing rate. This framework provides a general, task independent, account of variability in mean response latencies, with minimal theoretical commitments. It implies a positive correlation between the mean and standard deviation of mean latencies in that tasks associated with longer mean latencies also have a larger variance of mean latency across subjects. It also implies that individual differences in information processing rates will cause mean latencies to be positively correlated with each other.

This paper illustrates the consequences of these associations for the MLD. We develop a method of analysis to show that these associations bias correlations involving the MLD and make its interpretation problematic. Further, the analysis also shows that a variety of transformations fail to ameliorate these biases. Finally, we briefly introduce an alternative approach that is based on scale invariant contrasts of within-subject response latency distributions.

1. Method of analysis

In this section we develop the methodology for evaluating the properties of correlations involving the MLD. We obtain a general expression for the correlation between two linear combinations. This expression is a function of several parameters, including standard deviation ratios and correlations. Expressions for specific MLD correlations are obtained by fixing certain parameters to appropriate constants. The domain of latency data is defined in terms of the remaining free parameters. MLD correlations are analyzed, within the latency data domain, via visual function plots and linear models that estimate the marginal effect of each free parameter.

1.1. The correlation between linear combinations

Correlations involving the MLD are special cases of the correlation between L_1 and L_2, linear combinations of random variable pairs (X_1, Y_1) and (X_2, Y_2) that are weighted by coefficients (α_1, β_1) and (α_2, β_2).

$$L_1 = \alpha_1 X_1 + \beta_1 Y_1, \qquad L_2 = \alpha_2 X_2 + \beta_2 Y_2 \tag{1}$$

$$\text{Define } \lambda_1 = \frac{\sigma_{Y_1}}{\sigma_{X_1}}, \qquad \lambda_2 = \frac{\sigma_{Y_2}}{\sigma_{X_2}}, \qquad \lambda_X = \frac{\sigma_{X_2}}{\sigma_{X_1}} \tag{2}$$

$$\sigma_{Y_1} = \lambda_1 \sigma_{X_1}, \qquad \sigma_{X_2} = \lambda_X \sigma_{X_1}, \qquad \sigma_{Y_2} = \lambda_2 \lambda_X \sigma_{X_1} \tag{3}$$

$r_{X_1Y_1}, r_{X_2Y_2}, r_{X_1X_2}, r_{Y_1Y_2}, r_{X_1Y_2}, r_{X_2Y_1}$ are the correlations among X_1, Y_1, X_2, Y_2.

$$\sigma^2_{L_1+L_2} = \sigma^2_{L_1} + \sigma^2_{L_2} + 2\sigma_{L_1}\sigma_{L_2} r_{L_1L_2} \tag{4}$$

$$\sigma^2_{L_1} = \sigma^2_{\alpha_1X_1+\beta_1Y_1} = \alpha_1^2\sigma^2_{X_1} + \beta_1^2\sigma^2_{Y_1} + 2\alpha_1\beta_1\sigma_{X_1}\sigma_{Y_1}r_{X_1Y_1} = \sigma^2_{X_1}\left(\alpha_1^2 + \beta_1^2\lambda_1^2 + 2\alpha_1\beta_1\lambda_1 r_{X_1Y_1}\right) \tag{5}$$

$$\begin{aligned}\sigma^2_{L_2} &= \sigma^2_{\alpha_2X_2+\beta_2Y_2} = \alpha_2^2\sigma^2_{X_2} + \beta_2^2\sigma^2_{Y_2} + 2\alpha_2\beta_2\sigma_{X_2}\sigma_{Y_2}r_{X_2Y_2} \\ &= \sigma^2_{X_1}\lambda_X^2\left(\alpha_2^2 + \beta_2^2\lambda_2^2 + 2\alpha_2\beta_2\lambda_2 r_{X_2Y_2}\right).\end{aligned} \tag{6}$$