

SECOND EDITION

Sensory Discrimination Tests and Measurements

Sensometrics in Sensory Evaluation

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12 Measurements of sensory thresholds

12.1 Introduction

Threshold and sensitivity analysis is an important area of consumer and sensory research. As pointed out by Macmillan (2001), the estimation of threshold is the oldest project in psychophysics, and the search for appropriate methodology has almost as long a history.

Threshold is often thought of as the stimulus intensity that defines the lower limit of sensitivity of the sensory system. Stimulus intensity below that level is assumed not to have enough effect (detection or difference) on the sensory system to be perceived. The intuitive appeal of this idea is that there must be some absolute value below which the sensitivity of sensory system does not permit detection. Optimally, the threshold is thought of as a sharp transition point between sensation and no sensation. Inherent in the idea of a threshold is the assumption that the transition point is independent of conditions. In practice, the response of the system is affected by many psychological and physiological inputs, and shifts in the transition point (if it exists) may occur. This makes measurement of the threshold difficult and the transition point hard to define.

According to modern threshold theory, response to a stimulus, measured by proportion of correct response, is a random variable. Threshold is defined as a stimulus concentration (dose) that leads to a selected probability of correct response based on a dose–response model. Dose–response models are well-developed statistical methods and are widely applied in many fields, particularly in biological assay, toxicology, and pharmacology. They refer to the relationship between dose (a continuous variable) and response (usually a binary variable). The dose may represent the amount, duration, or intensity of exposure or treatment, and the response may represent binary expectation and effect. Under a dose–response model, the ED_{100p} value (a dosage corresponding to $100p\%$ probability of responses) can be estimated. The ED_{50} , which is the median effect dose, is usually defined as a threshold. Estimating ED_{100p} and its confidence interval is the main objective of sensitivity analysis.

Note that there are some major differences between dose–response models and typical toxicology studies in carrying out sensory sensitivity analyses. A sensory sensitivity experiment using the yes/no method may involve both sensitivity and decision criteria. The decision criterion concerning how large a difference can be judged a “difference” may affect a panelist’s response. Forced-choice methods, which can eliminate response bias, are often used for detection of sensory sensitivity. In a sensory sensitivity experiment using a forced-choice method, an independent background effect (i.e., the guessing probability) should be considered. Moreover, the proportion of correct responses depends

upon the method used. The same proportion of correct responses for different methods corresponds to different sensory differences. In other words, the same sensory difference corresponds to different proportions of correct responses in different methods. Hence, different ED_{100p} s may be needed for different methods in order to measure sensory sensitivity (see, e.g., Morrison 1982). As defined by Klein (2001), threshold is the stimulus strength that gives a fixed Thurstonian discriminial distance $d' = 1$. Hence, the corresponding probability of correct response should be 0.76 for the Two-Alternative Forced Choice (2-AFC), 0.63 for the Three-Alternative Forced Choice (3-AFC), 0.58 for the Duo-Trio, and 0.42 for the Triangular method.

There are different types of sensitivity, including individual, group, and population sensitivity. Different designs are required for estimations of the different types. In individual sensitivity analysis, all data are collected from an individual panelist. In group sensitivity analysis, the pooled data from panel members can be used under the assumption that the members all have similar sensitivities. In population sensitivity analysis, different batches of subjects are needed at different dosage levels, because the responses at different dosage levels should be independent. Estimated individual, group, and population sensitivities can be interpreted and used only for the corresponding individual, group, and population.

Different dose-response models exist, including parametric and nonparametric models (see, e.g., Powers and Ware 1976, Bi and Ennis 1998). ASTM international standard practice E679 (ASTM 2004a) describes one of the nonparametric methods, while ASTM international standard practice E1432 (ASTM 2004b) is based on a parametric model. The parametric model based on logistic regression and maximum likelihood is a very popular and useful model and can be regarded as a standard dose-response model. We discuss this model in Section 12.2 and some adopted models in the following sections. These include models for responses using forced-choice and unforced-choice methods for sensory sensitivity (Section 12.3) and a model for overdispersed responses for population sensitivity (Section 12.4). The main references are the books *Probit Analysis* (Finney 1971) and *Analysis of Quantal Response Data* (Morgan 1992).

12.2 Standard dose-response model

The logit (also called logistic) model in equation (12.2.1) is regarded as a standard dose-response mode. Suppose that there are k doses in a sensitivity experiment and that the i th dose, d_i , is given to n_i individuals, of whom r_i respond (respond “1” for the possible binary responses “0” and “1”). If $P(d_i)$ denotes the probability that any individual responds at the i th dose, under the assumption of independence between individuals within doses and between doses, the logistic regression can be used to model the relationship between $P(d_i)$ and d_i . A logarithmic dose transformation ($\log_{10}(dose)$) is often used to improve the fit of a logit model.

$$P(d_i) = \frac{1}{1 + e^{-\beta_0 - \beta_1 d_i}} \quad (12.2.1)$$

The logit transformation, a linearization of the logit model, is:

$$\log \left(\frac{P(d_i)}{1 - P(d_i)} \right) = \beta_0 + \beta_1 d_i \quad (12.2.2)$$