TRAIN YOUR BRAIN TO BEHAVE: CLINICAL APPLICATIONS OF NEUROFEEDBACK. Kathryn. N. Hoey, Dept. of Psychology, Christopher Newport University, Newport News, VA 23606. Neurofeedback (NF) is an operant-conditioning system, known as neuroregulation, which teaches individuals how to control or change their own brain activity. When an individual is diagnosed with a disorder that can be treated via neurofeedback, that patient can then seek out a clinical psychologist or other practicing therapist for neurofeedback treatment. The therapist will begin the treatment with a comprehensive qualitative EEG (qEEG) to gather the data necessary in order to devise a treatment program for that particular patient. Disorders that can be treated using neurofeedback include but are not limited to ADHD, cerebral palsy, migraines, and epilepsy. Each disorder is treated with specific neurofeedback protocols that target specific areas of the brain in order to achieve a specific change in brain functioning.

Statistics

SUPPORT VECTOR MACHINES WITH THE RAMP LOSS AND THE HARD MARGIN LOSS. J.P. Brooks, Dept. of Stat. Sci. and O.R., Virginia Commonwealth University, Richmond, VA 23284. The support vector machine (SVM) is a well-established method for classification based on an approach that emphasizes minimizing misclassification error while maximizing the distance between sets of correctly classified observations. In training models, SVM uses a measure of error that is based on the Euclidean distance of observations from the separating surface. In the interest of increasing the robustness of SVM, we present two new integer programming formulations that incorporate the ramp loss and the hard margin loss, respectively. These formulations are able to accommodate nonlinear kernel functions that have made traditional SVM popular. The consistency of SVM with these loss functions is established. Analysis of simulated and real-world data sets indicates that Ramp Loss SVM is preferred over both Hard Margin Loss SVM and the traditional Hinge Loss SVM in the presence of outliers when a low-rank kernel function is employed.

EVALUATING STATISTICAL SIGNIFICANCE IN SUPERSATURATED DESIGNS. David J. Edwards, Dept. of Statistical Sciences and Operations Research, Virginia Commonwealth University, Richmond, VA 23284 & Robert W. Mee, Dept. of Statistics, Operations, and Management Science, Univ. of Tennessee, Knoxville, TN 37996. Two-level supersaturated designs (SSDs) are designs that examine more than n-1 factors in n runs. Although literature involving the construction of SSDs is plentiful, less has been written about analysis of data from these designs. Perhaps this is due in large part to the dearth of actual applications. Whether using forward selection or all-subsets regression, it is easy to select models from SSDs that explain a very large percentage of the total variation. Hence, naïve p-values can persuade the user that included factors are indeed active. We propose the use of a global model randomization test in conjunction with all-subsets to more appropriately select candidate models of interest. For settings where the number of factors is too large for repeated use of all-subsets to be applied repeatedly, we propose a short-cut approximation for the p-values based on the beta distribution. Finally, we propose a randomization test for reducing the number of terms in candidate models with small global p-values.

USING SIMULATION OPTIMIZATION TO CONSTRUCT EFFICIENT SCREENING STRATEGIES FOR CERVICAL CANCER. Laura A. McLay & Chris Foufoulides, Dept. of Stats. & Oper. Res., Virginia Commonwealth Univ. Cervical cancer is the second most common type of cancer in women worldwide. Because cervical cancer is usually asymptomatic until the disease is in its advanced stages, cervical screening is of central importance towards combating cervical cancer. Alternative screening strategies are evaluated from an economic point of view through cost-effectiveness analysis. In the literature, however, studies perform cost-effectiveness analysis on a limited number of de facto screening policies. At present, no attempt has been made to construct efficient screening strategies through optimization, before cost-effectiveness analysis is applied. In this study simulation optimization is used to construct efficient screening strategies for cervical cancer by properly timing the screenings. The constructed strategies are highly cost-effective when a small number of lifetime screenings is available, and are more cost-effective than screening strategies used in practice or considered in the literature so far, indicating the value of optimal timing for other screened diseases as well.

EVALUATING THE ASYMPTOTIC LIMITS OF THE DELETE-A-GROUP JACKKNIFE FOR MODEL ANALYSES. Phillip S. Kott, National Agricultural Statistics Service, Department of Agriculture, Fairfax VA 22030 & Steven T. Garren, Department of Mathematics and Statistics, James Madison University, Harrisonburg VA 22807. The delete-a-group jackknife can be effectively used when estimating the variances of statistics based on a large sample. The theory supporting its use is asymptotic, however. Consequently, analysts have questioned its effectiveness when estimating parameters for a small domain computed using only a fraction of the large sample at hand. We investigate this issue empirically by focusing on heavily poststratified estimators for a population mean and a simple regression coefficient, where the poststratification take place at the full-sample level. Samples are chosen using differentially-weighted Poisson sampling. The bias and stability of delete-a-group jackknife employing either 15 of 30 replicates are evaluated and compared with the behavior of linearization variance estimators.

INFORMATION REDUCTION FOR BIAS AND VARIANCE ESTIMATION. Leonard A. Stefanski, Dept. of Stat., N.C. State Univ., Raleigh, NC 27696-8203. The jackknife and bootstrap are two well-known methods of reducing bias and estimating variance. Simulation-extrapolation is a method of reducing bias and estimating variance in measurement error models that works by adding more error to the observed data. Omitting an observation (jackknife), sampling from the observed data (bootstrap), and adding noise to data (simulation-extrapolation) are all ways of reducing information in a data set. In this talk I show that all three methods are conceptually similar when viewed in terms of information reduction, and argue that doing so is sometimes advantageous.