Editorial

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A brief ode to the empirical likelihood concept

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Statistical strategies to make decisions via formal rules play important roles in biostatistical discovery. When the forms of data distributions are specified, the likelihood ratio principle is a central doctrine for developing statistical decision-making mechanisms in clinical experiments. Neyman and Pearson provided strong arguments that show the likelihood ratio principle can lead to most powerful statistical decision-making rules according to the Neyman-Pearson lemma.[1] However, it is well known that when key assumptions are not met, parametric likelihood procedures may be suboptimal or biased. One very important issue in biostatistical research is to preserve efficiency of the statistical inference through the use of robust likelihood-type techniques. Towards this end, the modern biostatistical literature has shifted focus towards robust and efficient nonparametric likelihood methods.[2] The empirical likelihood (EL) methodology employs the likelihood concept in a distribution-free manner, approximating optimal parametric likelihood-based procedures. Since EL techniques and parametric likelihood methods are closely related concepts, one may apply corresponding EL functions to replace their parametric likelihood counterparts in known and well developed parametric procedures, e.g. constructing novel nonparametric Bayesian inference[3] and the confidence interval estimation.[4] This provides the impetus for an impressive expansion in the number of EL developments based on combinations of likelihoods of different types, e.g., when incomplete data should be analyzed, nonparametric likelihood ratio techniques can be combined with parametric likelihoods.[5]

The classical EL methodology, which is a distribution function-based approach, has been shown to have attractive properties for testing hypotheses regarding parameters (e.g. moments) of distributions.[6] In practice, statisticians commonly face a variety of distribution-free comparisons and/or evaluations over all distribution functions of complete and incomplete data subject to different types of measurement errors. In these frameworks, the density-based EL methodology is shown to be very efficient.[7-10] According to the Neyman-Pearson lemma, the most powerful test statistics have structures that are related to density-based likelihood ratios. The density-based EL method can be easily and satisfactorily applied to construct highly efficient test procedures, approximating non-parametrically most powerful Neyman-Pearson test-rules, given aims of clinical studies. Similarly to the parametric likelihood concept, the EL methodology provides relatively simple strategies to construct powerful statistical tests that can be applied in various complex biostatistical studies. The extreme generality of EL methods and their wide ranges of usefulness partly result from the simple derivation of the EL statistics as components of composite parametric and nonparametric likelihood based systems, efficiently attending to any observed data and relevant information. The EL based methods are employed in much of modern biostatistical practice.

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Conflict of Interest

None.

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