

# Properties of $L^1$ residuals

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*Abstract:* The paper discusses the behavior of residuals from least-absolute-deviations (or  $L^1$ ) fits of linear models. Particular emphasis is given to data arising by way of designed experiments. The paper argues that the  $L^1$  method of fitting such models should be discouraged. The method is inefficient when compared to other robust methods while not being any simpler to compute. The residuals obtained by  $L^1$  fitting exhibit several weaknesses. First of all they are ambiguous in the sense that there are a multitude of  $L^1$  fits, sometimes quite far apart. Second, typical algorithms produce as many exact zero residuals as there are contrasts fitted. As a result, the non zero residuals do not give an accurate reflection of the errors that occurred during the experimental runs.

*Key words:* Least absolute deviations, factorial designs, outliers detection, uniqueness of fit.

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## 1 Introduction

Let  $y = X\theta + \varepsilon$  be a linear model with uncorrelated, centered, and homoskedastic errors  $\varepsilon_1, \dots, \varepsilon_n$ . As indicated, we take  $n$  to be the number of observations, whereas  $p$  denotes the dimension of the regression parameter  $\theta$ . The least-squares residuals are  $r = (I - H)y$ , where  $\hat{y} = Hy = X(X^T X)^{-1} X^T y$  is the least-squares fit. If the error distribution has two moments, it follows that  $E(r) = X\theta - HX\theta = 0$ , and  $Var(r) = \sigma^2(I - H)$ . The use of such residuals for outlier detection and other diagnostic purposes has been explored in great detail in the statistical literature (see for example Belsley, Kuh and Welsch, 1980; Cook and Weisberg, 1982).

Residuals from an  $L^1$  fit are not so easily described. Throughout this article, we denote by  $\tilde{\theta}$  a parameter fit obtained by minimizing the least-