of the original error terms, e_i. The procedure suggested in Section 7 is an attempt to ensure that the error terms associated with x_i in the bootstrap samples capture some of the possible dependence on x_i. This approach leads to the "bootstrap" estimator for the covariance of $\tilde{\beta}$ being $V_{J(1)}$, and so this resampling method is as effective as the weighted jackknife in this regard. The potential advantage the bootstrap procedure has over the jackknife in general is in approximating the distribution of $(\hat{\beta} - \beta)$. In the case where the e_i's are independent and identically distributed the procedure suggested in Section 7 forces some arbitrary distribution on y_i^* through t_i^*, and the actual distribution of the e_i's is lost. Thus, the usefulness of this approach in generating confidence intervals by approximating the distribution of $(\hat{\beta} - \beta)$ is in question. Perhaps the jackknife–bootstrap hybrid is the answer to this problem and this model certainly deserves more investigation.

The bootstrap percentile method for calculating confidence intervals in regression has been investigated by Robinson (1985). He compared the bootstrap approach to the exact confidence intervals obtained by inverting permutation tests and suggested an adjustment to the bootstrap percentile method to improve its coverage probability.

The use of t-confidence intervals in the simulation study for the parameter $\theta = -\beta_1/2\beta_2$ should give moderate results with normal errors and β_2 away from 0. Weber and Welsh (1983) found that the standardised distribution of the jackknife statistic for θ can be very skewed and so one would not expect the symmetric t-confidence interval to give reasonable coverage in general. The adjusted percentile methods appear to be the appropriate way of obtaining nonparametric confidence intervals for θ.

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Along with commenting on this authoritative paper, we wish to make a plea for an approach to the computational problems of resampling and simulation