According to Dudley's (1978) Theorem 7.1, the last term of (12) is $o_p(n^{-1/2})$. Next turn attention to the fourth term and note that

$$
\begin{aligned}
&\operatorname{Var}\bigl(E_{\bar{X}^*}\{G_P\{[-\sigma t, \bar{X}^* - St]\}\}\bigr)\\
&\quad\le \operatorname{Var}\bigl(G_P\{[-\sigma t, \bar{X}^* - St]\}\bigr)\\
&\quad= \operatorname{Var}\bigl(E\{G_P\{[-\sigma t, \bar{X}^* - St]\}|\bar{X}^*, S\}\bigr)\\
&\qquad+E\{\operatorname{Var}\bigl(G_P\{[-\sigma t, \bar{X}^* - St]\}|\bar{X}^*, S\bigr)\}
\end{aligned}
\tag{13}
$$

in view of the conditional variance formula. The first term of (13) is 0 because G_P is a mean 0 process, while the second term is less than $E\{|F(-\sigma t) - F(\bar{X}^* - St)|\} = o(1)$. Therefore, in view of (9) and (12),

$$
\begin{aligned}
&P\left\{\frac{\bar{X} - Z}{\sigma} \le t\right\} - P^*\left\{\frac{\bar{X}^* - Z^*}{S} \le t\right\}\\
&\qquad= F_n(-\sigma t) - F(-\sigma t) + \bar{X}F'(-\sigma t) + (\sigma - S)tF'(-\sigma t) + o_p(n^{-1/2}),
\end{aligned}
$$

which is of exact order $n^{-1/2}$ in probability as a consequence of the central limit theorem.

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Peter Hall's paper gives a welcome and illuminating comparison of competing bootstrap confidence intervals for a one-dimensional parameter. Though important, this one-dimensional case is very special in several respects. Techniques such as Studentizing or accelerated bias correction do not generalize readily to confidence sets for a multidimensional parameter. I will address two problems: (i) how to construct analogs of second-order correct bootstrap confidence sets when the parameter θ is vector-valued or infinite-dimensional and (ii) how the general approach for multidimensional θ relates to the one-dimensional methods discussed by Hall.

1. Consider the following setting: The sample x_n has distribution $P_{n,\lambda}$ which depends upon an unknown parameter λ; the dimension of λ may be infinite: Of interest is the parametric function $\theta = T(\lambda)$, which need not be scalar-valued. Let $R_n(\theta) = R_n(x_n, \theta)$ be a confidence set root for θ—a real-valued function of the sample and of θ. Let $J_n(\cdot, \lambda)$ denote the left-continuous cdf of R_n. Suppose