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**Algorithm 1:** Algorithm for Jackknife Variance Estimator
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$df \leftarrow n \times p$ matrix with missing observations.

$df_m^i$ is the $m^{th}$ imputed dataset.

$df^j$ is the $j^{th}$ jackknife sample with $d$ observation dropped.

In many cases $\binom{n}{d}$ is a large value, which makes obtaining all possible jackknife subsamples infeasible. As such, an arbitrarily large number of subsamples are generated, denoted by $j$.

Impute $df$ $m$ times to obtain $m$ complete datasets.

**Imputations** ← **for** *1* **to** $m$ **do**
   |   Create $j$ jackknife subsamples from the $m^{th}$ dataset, resulting in
   |   $j \times m$ subsamples of size $n - d$
**end**

**Point estimates** ← **for** *1* **to** $j \times m$ **do**
   |   Apply analysis model to **Imputations** to obtain a vector of length
   |   $j \times m$ containing estimates.
**end**

$$\hat{\theta}_{jack} = \frac{1}{j \times m} \sum_{i=1}^{j \times m} \hat{\theta}_i \tag{1}$$

Finally, the confidence interval will take on the form

$$(\hat{\theta}^{\alpha/2}, \hat{\theta}^{1-(\alpha/2)}) \tag{2}$$

In general, $m < 5$ while $\sqrt{n} << d < n$ is sufficient. However, for statistics sensitive to subtle changes between the different jackknife subsamples (such as the various percentiles), values for $m$, $d$, and $j$ should be adjusted.
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