Algorithm 1: Algorithm for Jackknife Variance Estimator

$df \leftarrow n \times p$ 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.

Imputations $\leftarrow$ **for** *1* **to** m **do**

  Create j jackknife subsamples from the observed dataset, resulting in j subsamples of size $n - d$, and impute each subsample m times, resulting in $m \times j$ complete datasets.

end

Point estimates $\leftarrow$ **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.