Algorithm 1: Algorithm for Sequential Jackknife Variance Estimator

$df \leftarrow n \times p$ matrix with missing observations.

df^i_m is the m^{th} imputed dataset.

l^{-m} is the list of imputed dataframes with the m^{th} one removed.

$df^j \in l^{-m}$ is the j^{th} jackknife sample with k observation dropped.

In many cases $\binom{n}{k}$ 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.

for *1* **to** m **do**
  Generate l^{-m} of size $\binom{m}{m-1}$ where the m^{th} imputed dataset is excluded.
end

for *1* **to** $\binom{m}{m-1}$ **do**
  Apply analysis model to obtain a vector of length j containing estimates.
end

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

Finally, the confidence interval will take on the form

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

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