Generally, $\sigma^{2}$ will not be known and must be estimated from the data by calculating the pooled sample variance,

$$
s_{p}^{2}=\frac{(n-1) s_{X}^{2}+(m-1) s_{Y}^{2}}{m+n-2}
$$

where $s_{X}^{2}=\left(n-\overline{\bar{Y} \sum_{i=1}^{n}}\left(X_{i}-\bar{X}\right)^{2}\right.$ and similarly for $s_{Y}^{2}$. Note that $s_{p}^{2}$ is a weighted average of the sample variances of the $X^{\prime}$ 's and $Y$ 's, with the weights proportional to the degrees of freedom. This weighting is appropriate since if one sample is much larger than the other, the estimate of $\sigma^{2}$ from that sample is more reliable and should receive greater weight. The following theorem gives the distribution of a statistic that will be used for forming confidence intervals and performing hypothesis tests.

## THEOREM A

Suppose that $X_{1}, \ldots, X_{n}$ are independent and normally distributed random variables with mean $\mu_{X}$ and variance $\sigma^{2}$, and that $Y_{1}, \ldots, Y_{m}$ are independent and normally distributed random variables with mean $\mu_{Y}$ and variance $\sigma^{2}$, and that the $Y_{i}$ are independent of the $X_{i}$. The statistic

$$
t=\frac{(\bar{X}-\bar{Y})-\left(\mu_{X}-\mu_{Y}\right)}{s_{p} \sqrt{\frac{1}{n}+\frac{1}{m}}}
$$

follows a $t$ distribution with $m+n-2$ degrees of freedom.

## Proof

According to the definition of the $t$ distribution in Section 6.2, we have to show that the statistic is the quotient of a standard normal random variable and the square root of an independent chi-square random variable divided by its $n+m-2$ degrees of freedom. First, we note from Theorem B in Section 6.3 that $(n-1) s_{X}^{2} / \sigma^{2}$ and $(m-1) s_{Y}^{2} / \sigma^{2}$ are distributed as chi-square random variables with $n-1$ and $m-1$ degrees of freedom, respectively, and are independent since the $X_{i}$ and $Y_{i}$ are. Their sum is thus chi-square with $m+n-2$ df. Now, we express the statistic as the ratio $U / V$, where

$$
\begin{aligned}
U & =\frac{(\bar{X}-\bar{Y})-\left(\mu_{X}-\mu_{Y}\right)}{\sigma \sqrt{\frac{1}{n}+\frac{1}{m}}} \\
V & =\sqrt{\left[\frac{(n-1) s_{X}^{2}}{\sigma^{2}}+\frac{(m-1) s_{Y}^{2}}{\sigma^{2}}\right] \frac{1}{m+n-2}}
\end{aligned}
$$

$U$ follows a standard normal distribution and from the preceding argument $V$ has the distribution of the square root of a chi-square random variable divided by its degrees of freedom. The independence of $U$ and $V$ follows from Corollary A in Section 6.3.

