# Theoretical errors 

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#### Abstract

How to evaluate theoretical errors out of a $\chi^{2}$ analysis


## 1 Hesse matrix

Consider a theoretical approach which dependens on $N$ unknown parameters $x_{1}, x_{2}, \ldots, x_{N}$. We can determine them by searching the minimum of

$$
\begin{align*}
\chi^{2}\left[x_{1}, \ldots x_{N}\right]= & \left(\frac{A_{1}\left[x_{1}, \ldots, x_{N}\right]-A_{1}^{\exp }}{\delta A_{1}}\right)^{2}+  \tag{1}\\
& \left(\frac{A_{2}\left[x_{1}, \ldots, x_{N}\right]-A_{2}^{\exp }}{\delta A_{2}}\right)^{2}+\ldots+\left(\frac{A_{q}\left[x_{1}, \ldots, x_{N}\right]-A_{q}^{\exp }}{\delta A_{q}}\right)^{2}(2) \\
= & \sum_{i=1}^{Q}\left(\frac{A_{i}\left[x_{1}, \ldots, x_{N}\right]-A_{i}^{\exp }}{\delta A_{i}}\right)^{2} \tag{3}
\end{align*}
$$

where $A_{i}\left[x_{1}, \ldots, x_{N}\right]$ are the theoretical expressions $(Q \geqslant N)$ for which there are experimental measurements $\delta A_{i}$.

Let the point $\left\{x_{1}^{\min }, \ldots, x_{N}^{\min }\right\}$ be the minimum of $\chi^{2}$ realized at the point $\left\{x_{1}^{\min }, \ldots, x_{N}^{\min }\right\}$. We introduce the new variables $y_{i}$ :

$$
\vec{y}=\left(\begin{array}{c}
y_{1}  \tag{4}\\
\vdots \\
y_{N}
\end{array}\right)=\left(\begin{array}{c}
x_{1}-x_{1}^{\min } \\
\vdots \\
x_{N}-x_{N}^{\min }
\end{array}\right)=\vec{x}-\vec{x}^{\min }
$$

In therms of the variables $y_{i}$ the minimum is obviously realized at $P=\{0, \ldots 0\}$.
Let us now write the Taylor expansion of $\chi^{2}$ around $y_{i}=0$ :

$$
\begin{equation*}
\chi^{2}[y]=\chi_{0}^{2}+y^{t} H y \tag{5}
\end{equation*}
$$

where the Hesse matrix $H$ is given by:

$$
\begin{equation*}
H_{i j}=\frac{1}{2}\left(\frac{\partial^{2} \chi^{2}\left[y_{1}, \ldots y_{N}\right]}{\partial y_{i} \partial y_{j}}\right)_{P}=\cdot \frac{1}{2}\left(\frac{\partial^{2} \chi^{2}\left[x_{1}, \ldots y_{N}\right]}{\partial x_{i} \partial x_{j}}\right)_{P} \tag{6}
\end{equation*}
$$

Note, we have used the fact the the first derivative vanishes: $\left(\frac{\partial \chi^{2}\left[y_{1}, \ldots y_{n}\right]}{\partial y_{i}}\right)_{P}=$ 0.

## 2 Diagonalization

We now introduce new variables $z_{i}$ in the following way:

$$
\vec{z}=\left(\begin{array}{c}
z_{1}  \tag{7}\\
\vdots \\
z_{N}
\end{array}\right)=B\left(\begin{array}{c}
y_{1} \\
\vdots \\
y_{N}
\end{array}\right)=B \vec{y}=B\left(\vec{x}-\vec{x}^{\min }\right)
$$

with $B \subset S O(N)$ in such a way that

$$
\begin{equation*}
B H B^{t}=\lambda=\operatorname{diag}\left\{\lambda_{1}, \ldots, \lambda_{N}\right\} \tag{8}
\end{equation*}
$$

where $\lambda_{1}, \ldots, \lambda_{n}$ are the eigenvalues of the matrix $H$. Note, the matrix $B$ can be written as

$$
B=\left(\begin{array}{ccc}
\frac{\partial z_{1}}{\partial x_{1}} & \frac{\partial z_{1}}{\partial x_{2}} & \cdots  \tag{9}\\
\frac{\partial z_{2}}{\partial x_{1}} & \frac{\partial z_{2}}{\partial x_{2}} & \cdots \\
\cdots & \cdots & \cdots
\end{array}\right)_{P}
$$

and

$$
B^{t}=\left(\begin{array}{ccc}
\frac{\partial x_{1}}{\partial z_{1}} & \frac{\partial x_{1}}{\partial z_{2}} & \cdots  \tag{10}\\
\frac{\partial x_{2}}{\partial z_{1}} & \frac{\partial x_{2}}{\partial z_{2}} & \cdots \\
\cdots & \cdots & \cdots
\end{array}\right)_{z_{i}=0}
$$

The quantity $\chi^{2}$ expressed in terms of $z_{i}$ takes the simple form:

$$
\begin{align*}
\chi^{2}[z] & =\chi_{0}^{2}+z^{t} B H B^{t} z=\chi_{0}^{2}+z^{t} \lambda z= \\
& =\chi_{0}^{2}+z_{1}^{2} \lambda_{1}+\ldots+z_{N}^{2} \lambda_{N} . \tag{11}
\end{align*}
$$

The errors on the quantities $z_{i}$ are now easily given by

$$
\begin{equation*}
\delta z_{i}=\frac{1}{\sqrt{\lambda_{i}}} \tag{12}
\end{equation*}
$$

which correspond to a variation of $\pm 1$ for the $\chi^{2}$ :

$$
\begin{equation*}
\chi^{2}\left[0,0, \ldots, z_{i}= \pm \frac{1}{\sqrt{\lambda_{i}}}, 0, \ldots 0\right]=\chi_{0}^{2}+1 \tag{13}
\end{equation*}
$$

If we shift at the same time all the quantities $z_{i}$ we obtain

$$
\begin{equation*}
\chi^{2}\left[ \pm \frac{1}{\sqrt{\lambda_{1}}} \ldots, z_{i}= \pm \frac{1}{\sqrt{\lambda_{i}}}, \ldots, \pm \frac{1}{\sqrt{\lambda_{N}}}\right]=\chi_{0}^{2}+N \tag{14}
\end{equation*}
$$

This is the maximum variation allowed.

## 3 Error calculation for a generic function $F$

Now, all the theoretical quantities we would like to determine are -most probablyfunction of the original parameters $x_{i}$. Let us consider, for instance, some function

$$
\begin{equation*}
F=F\left[x_{1}, \ldots, x_{N}\right] \tag{15}
\end{equation*}
$$

which we want to determine. The central value is easy:

$$
\begin{equation*}
F_{0}=F\left[x_{1}^{\min }, \ldots, x_{N}^{\min }\right] \tag{16}
\end{equation*}
$$

The problem is how to calculate the error $\delta F$. In fact, we know the errors only in terms of the variables $z_{i}$, thus we should re-express $F$ as function $F=F[z]$ and evaluate

$$
\begin{equation*}
\delta F=\sqrt{\left(\frac{\partial F}{\partial z_{1}} \delta z_{1}\right)^{2}+\ldots+\left(\frac{\partial F}{\partial z_{n}} \delta z_{n}\right)^{2}} \tag{17}
\end{equation*}
$$

Instead of doing it explicitly we notice that

$$
\begin{equation*}
\frac{\partial F}{\partial z_{1}}=\frac{\partial F}{\partial x_{1}} \frac{\partial x_{1}}{\partial z_{1}}+\ldots+\frac{\partial F}{\partial x_{N}} \frac{\partial x_{N}}{\partial z_{1}} \tag{18}
\end{equation*}
$$

where the derivatives $\frac{\partial x_{1}}{\partial z_{1}}, \ldots, \frac{\partial x_{n}}{\partial z_{1}}$ are the first column of the matrix $B^{t}$.
We now present two ways to write $\delta F$.
Way 1 to write $\delta F$ in a compact form:
We introduce the vector

$$
\vec{f}=(\vec{\nabla} F)_{P}=\left(\begin{array}{c}
\frac{\partial F}{\partial x_{1}}  \tag{19}\\
\vdots \\
\frac{\partial F}{\partial x_{N}}
\end{array}\right)_{P}
$$

Then:

$$
\begin{align*}
\frac{\partial F}{\partial z_{1}} & =\frac{\partial F}{\partial x_{1}} \frac{\partial x_{1}}{\partial z_{1}}+\ldots+\frac{\partial F}{\partial x_{N}} \frac{\partial x_{N}}{\partial z_{1}}  \tag{20}\\
& =\left(\vec{f}^{t} B^{t}\right)_{1}=(B \vec{f})_{1}^{t}=(B \vec{f})_{1} \tag{21}
\end{align*}
$$

Ergo:

$$
\begin{equation*}
\delta F=\sqrt{\frac{1}{\lambda_{1}}(B \vec{f})_{1}^{2}+\ldots+\frac{1}{\lambda_{N}}(B \vec{f})_{N}^{2}} \tag{22}
\end{equation*}
$$

Way 2 to write $\delta F$ in a compact form:
It is useful to introduce the matrix $D$

$$
D=\left(\begin{array}{ccc}
\frac{\partial F}{\partial x_{1}} & \frac{\partial F}{\partial x_{2}} & \cdots  \tag{23}\\
\frac{\partial F}{\partial x_{1}} & \frac{\partial F}{\partial x_{2}} & \cdots \\
\cdots & \cdots & \cdots
\end{array}\right)_{x=x^{\min }}
$$

and then the matrix product

$$
\begin{equation*}
D \cdot B^{t} \cdot \lambda^{-1 / 2} \tag{24}
\end{equation*}
$$

We then pick up only the diagonal elements of the latter matrix and form the vector

$$
\alpha=\left(\begin{array}{c}
\left(D \cdot B^{t} \cdot \lambda^{-1 / 2}\right)_{11}  \tag{25}\\
\vdots \\
\left(D \cdot B^{t} \cdot \lambda^{-1 / 2}\right)_{N N}
\end{array}\right)
$$

Now, the error of the function $F$ is given by

$$
\begin{equation*}
\delta F=\sqrt{\alpha^{t} \alpha} \tag{26}
\end{equation*}
$$

When changing the function $F$ with another function $G$ all goes as before, provided that one recalculates the matrix $D$ as

$$
D=\left(\begin{array}{ccc}
\frac{\partial G}{\partial x_{1}} & \frac{\partial G}{\partial x_{2}} & \cdots  \tag{27}\\
\frac{\partial G}{\partial x_{1}} & \frac{\partial G}{\partial x_{2}} & \cdots \\
\cdots & \cdots & \cdots
\end{array}\right)_{x=x^{\min }}
$$

## 4 Error on the original parameters $x_{i}$

As a last step we consider a special case. We suppose that the function $G=x_{1}$. Using the way 2 described above, the matrix $D$ takes the form

$$
D=\left(\begin{array}{ccc}
1 & 0 & \ldots  \tag{28}\\
1 & 0 & \ldots \\
\cdots & \cdots & \cdots
\end{array}\right)
$$

One obtains the error on the original parameter $x_{1}$ :

$$
\begin{equation*}
\delta x_{1}=\sqrt{\left(\frac{\partial x_{1}}{\partial z_{1}} \frac{1}{\sqrt{\lambda_{1}}}\right)^{2}+\left(\frac{\partial x_{1}}{\partial z_{2}} \frac{1}{\sqrt{\lambda_{2}}}\right)^{2}+\ldots} \tag{29}
\end{equation*}
$$

Note that the latter can be obtained also in another way. To this end we recall that

$$
\begin{equation*}
B H B^{t}=\lambda \tag{30}
\end{equation*}
$$

Ergo:

$$
\begin{equation*}
B\left(B^{t} \lambda^{-1} B\right)=1 \tag{31}
\end{equation*}
$$

out of which we identify the inverse of the Hesse matrix:

$$
\begin{equation*}
H^{-1}=B^{t} \lambda^{-1} B \tag{32}
\end{equation*}
$$

Now, let us consider the element $H_{11}^{-1}$. With simple passages we obtain that

$$
\begin{equation*}
H_{11}^{-1}=\left(\frac{\partial x_{1}}{\partial z_{1}}\right)^{2} \frac{1}{\lambda_{1}}+\left(\frac{\partial x_{1}}{\partial z_{2}}\right)^{2} \frac{1}{\lambda_{2}}+\ldots \tag{33}
\end{equation*}
$$

and therefore

$$
\begin{equation*}
\delta x_{1}=\sqrt{H_{11}^{-1}} . \tag{34}
\end{equation*}
$$

The error on the original parameter $x_{1}$ is the first element of the inverse Hesse matrix. More in general

$$
\begin{equation*}
\delta x_{i}=\sqrt{H_{i i}^{-1}} \tag{35}
\end{equation*}
$$

i.e., the diagonal of the inverse Hesse matrix gives us the squared errors of the original parameters.

Note that, in virtue of the obtained $\delta x_{i}$, one would be tempted to calculate the error of a function $F$ as

$$
\begin{equation*}
\delta F_{\text {naive }}=\sqrt{\left(\frac{\partial F}{\partial x_{1}} \delta x_{1}\right)^{2}+\ldots+\left(\frac{\partial F}{\partial x_{N}} \delta x_{N}\right)^{2}} \tag{36}
\end{equation*}
$$

However, the variables $x_{i}$ do not diagonalize the Hesse matrix and correlations are not eliminated. One has therefore

$$
\begin{equation*}
\delta F_{\text {naive }} \geq \delta F \tag{37}
\end{equation*}
$$

The evaluation of $\delta F_{\text {naive }}$ is therefore an overestimate of the real error. In fact, we cannot vary the parameters $x_{i}$ as we want in the hypercube defined by $x_{i} \pm \delta x_{i}$ because in this way we neglect the correlations and we may reach value of $\chi^{2}$ which are much larger than the 'limit' $\chi_{0}^{2}+N$ evaluated above.

