## Modeling of Detes

- NRiC Chapter 15.
- Model depends on adjustable parameters.
- Can be used for "constrained interpolation".
- Basic approach:

1. Choose figure-of-merit function (e.g. $\chi^{2}$ ).
2. Adjust best-fit parameters: minimize merit function.
3. Compute error estimates for parameters.
4. Compute goodness-of-fit.
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- Suppose we want to fit $N$ data points $\left(x_{i}, y_{i}\right)$ with a function that depends on $M$ parameters $a_{j}$ and that each data point has a standard deviation $\sigma_{i}$. The maximum likelihood estimate of the model parameters is obtained by minimizing:

$$
x^{2}=\sum_{i=1}^{N}\left(\frac{y_{i}-y\left(x_{i} ; a_{1} a_{M}\right)}{\sigma_{i}}\right)^{2}
$$

- Assuming the errors are normally distributed, a "good fit" has $\chi^{2} \sim \nu$, where $v=N-M$.


## Fitting Detea to astraight Line

- For this case the model is simply:

$$
y(x)=y(x ; a, b)=a+b x
$$

- Derive formula for best-fit parameters by setting $\partial X^{2} / \partial a=0=\partial X^{2} / \partial b$.
- Derive uncertainties in $a$ and $b$ using:

$$
\sigma_{f}^{2}=\sum_{i=1}^{N} \sigma_{i}^{2}\left(\frac{\partial f}{\partial y_{i}}\right)^{2}
$$

- Want $Q=\operatorname{gammq}\left((N-2) / 2, \chi^{2} / 2\right)>0.001$.


## Cenereal Lineer Lesat Siquares

- Can generalize to any linear combination:

$$
\begin{gathered}
y(x)=\sum_{j=1}^{M} a_{j} X_{j}(x) \\
\text { e.g. } y(x)=a_{1}+a_{2} x+a_{3} x^{2}+\ldots+a_{M} x^{M-1}
\end{gathered}
$$

- Define $N \times M$ design matrix $A_{i j}=X_{j}\left(x_{i}\right) / \sigma_{i}$.
- Also define vector $\mathbf{b}$ of length $N: b_{i}=y_{i} / \sigma_{i}$ and vector a of length $M$ : $a_{i}=a_{1}, \ldots, a_{M}$.
- Then we wish to find a that minimizes:

$$
X^{2}=|A \mathbf{a}-\mathbf{b}|^{2} \leftarrow \text { This is what SVD solves! }
$$

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- Recall for SVD we had $A=U W V^{T}$.
- Rewriting the SVD solution we get:

$$
\mathbf{a}=\sum_{j=1}^{M}\left(\frac{U_{\left(c_{0}\right.} \mathbf{b}}{w_{j}}\right) V_{(j)}
$$

where $U_{(j)}$ and $V_{(j)}$ denote columns of $U$ and $V$.

- As before, if $w_{j}$ is small (or zero), can omit.
- Useful because least-squares problems are both overdetermined ( $N>M$ ) and underdetermined (ambiguous combinations of parameters exist)!
Nonilinear Models
- Suppose model depends nonlinearly on the $a_{j}$ 's...

$$
\text { e.g. } y(x)=a_{1} \exp \left(-a_{2} x^{2}\right) \text {. }
$$

- Still define $\chi^{2}$, but must proceed iteratively:
- Use $\mathbf{a}_{\text {next }}=\mathbf{a}_{\text {cur }}-\lambda \nabla \chi^{2}\left(\mathbf{a}_{\text {cur }}\right)$ far from minimum (steepest descent), where $\lambda$ is a constant.
- Use $\mathbf{a}_{\text {next }}=\mathbf{a}_{\text {cur }}-D^{-1}\left[\nabla \chi^{2}\left(\mathbf{a}_{\text {cur }}\right)\right]$ close to minimum, where $D$ is the Hessian matrix.
- The Levenberg-Marquardt method adjusts $\lambda$ to smooth the transition between these two regimes.
Leveniberg-MEarqueldt MIEthod
- $N R i C$ provides two routines, mrqmin() and mrqcof(), that implement the L-M method.
- The user must provide a function that computes $y$ $\left(x_{i}\right)$ as well as all the partial derivatives $\partial y / \partial a_{j}$ evaluated at $x_{i}$.
- The routine mrqmin() is called iteratively until a successful step (i.e. one in which $\lambda$ gets smaller) changes $\chi^{2}$ by less than a fractional amount, like 0.001 (no point in doing better).

