

⑥ If errors are uncorrelated, then the covariance is ideally zero,
(clocking error)

If errors are correlated (systematic bias in phase picking),
then the covariance is non-zero.

⑦ The data are inverted using the generalized inverse
solution

$$m_j = \sum_i G_{ji}^{-g} d_i \quad (31)$$

Covariance of the model parameter

$$\sigma_m^2 = \sigma_{m_j i}^2 = \lim_{K \rightarrow \infty} \frac{1}{K} \sum_{k=1}^K (m_j^{(k)} - \bar{m}_j) (m_i^{(k)} - \bar{m}_i)$$

$$= \lim_{K \rightarrow \infty} \frac{1}{K} \left[\sum_p G_{jp}^{-g} (d_p^{(k)} - \bar{d}_p) \right] \left[\sum_s G_{is}^{-g} (d_s^{(k)} - \bar{d}_s) \right]$$

$$= \sum_p G_{jp}^{-g} \sum_s G_{is}^{-g} \left[\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{k=1}^K (d_p^{(k)} - \bar{d}_p) (d_s^{(k)} - \bar{d}_s) \right]$$

$$= \sum_p G_{jp}^{-g} \sum_s G_{is}^{-g} \sigma_{d_p d_s}^2 \quad (32)$$

Or in matrix form.

$$\sigma_m^2 = G^{-g} \sigma_d^2 (G^{-g})^T \quad (33)$$

If we assume that the data errors are uncorrelated and equal, then $\sigma_d^2 = \sigma^2 \delta_{ij}$ 34

So the Model Variance-covariance matrix is

$$\sigma_m^2 = \sigma^2 (G^T G)^{-1} \quad (35)$$

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>Show Table 7.2. EQ location example with errors

9) In table 7.2.2, depth is less well constrained than the epicenter. Why?

10) The off-diagonal elements are non-zero, which means?

Ans: the uncertainties in the model parameter estimates are correlated

E.g. A trade-off between focal depth & origin time.

11) Error ellipse,

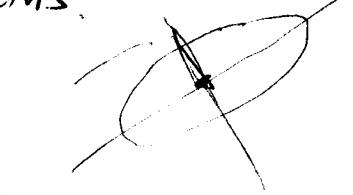
diagonalize it by finding the eigenvalues $\lambda^{(1)}$ and $\lambda^{(2)}$ and associated eigenvectors.

$$\begin{bmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 \end{bmatrix}$$

12) Behavior of the misfit function

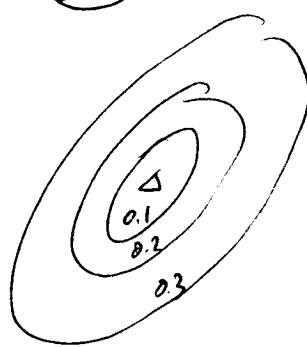
Around its minimum

$$\epsilon = \sum_{i=1}^n [t_i - t_i^p]^2$$



Depending on how ϵ grows:

If ϵ grows rapidly as we move away from the minimum point, we can resolve the location better than a slow growth.



(8)

To quantify this

We define.

$$\chi^2 = \sum_{i=1}^n \frac{[t_i - t_i^0]^2}{\sigma_i^2}$$

(37)

σ_i is the expected standard deviation of the i th residual due to random measurement error.

The expected value of χ^2 is \approx the number of degrees of freedom $ndf = \text{number of observations} - \text{number of parameters}$

Percentage Points of the χ^2 distribution

ndf	$\chi^2(95\%)$	$\chi^2(50\%)$	$\chi^2(5\%)$
5	1.15	4.35	11.07
10	3.94	9.34	18.31
20	10.85	19.34	31.41
50	34.76	49.33	67.50
100	77.93	99.33	124.34

The key is to get σ_i , sometimes the information is not available for a real experiment.

(9)

We could then estimate the standard deviation of the data from the fit between the data and the best fitting model.

$$\chi^2(m_{\text{best}}) = \frac{\sum_{i=1}^n [t_i - t_i^P(m_{\text{best}})]^2}{\text{ndf}}$$

(36)

Where m_{best} is the best-fitting location.

Then eq (37) becomes

$$\chi^2(m) = \frac{\sum_{i=1}^n [t_i - t_i^P(m)]^2}{\text{ndf}}$$

(37)

Note that $\chi^2(m_{\text{best}}) = \text{ndf}$ so that the χ^2 -value at the best-fit hypocenter is close to the 50% point in the χ^2 distribution. By contours $\chi^2(m)$, we can then estimate the 95% confidence ellipse.