Lecture 8 outline

The method of least squares

1. **Connection with maximum likelihood**
2. **Linear LS problem**
3. **LS fit of a polynomial**
4. **Testing goodness-of-fit with LS**
5. **LS with binned data**
6. **Combining measurements with LS**

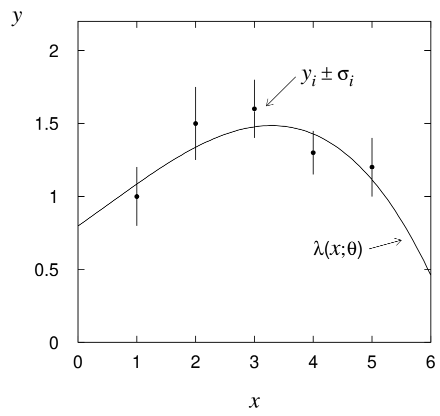
Connection with maximum likelihood

Suppose we have Gaussian r.v.s y_i, $i = 1, \ldots, N$

$E[y_i] = \lambda_i = \lambda(x_i; \vec{\theta})$,

where $x_1, \ldots, x_N$ and $V[y_i] = \sigma_i^2$ are known.

Goal: estimate parameters $\vec{\theta}$, i.e. fit the curve through the points.



The joint pdf for independent Gaussian y_i is

$$g(\vec{y}; \vec{\lambda}, \vec{\sigma}^2) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(\frac{-(y_i - \lambda_i)^2}{2\sigma_i^2} \right)$$

i.e. the log-likelihood function is (drop terms not depending on $\vec{\theta}$),

$$\log L(\vec{\theta}) = -\frac{1}{2} \sum_{i=1}^{N} \frac{(y_i - \lambda(x_i; \vec{\theta}))^2}{\sigma_i^2}$$

→ maximizing $\log L(\vec{\theta})$ same as minimizing

$$\chi^2(\vec{\theta}) = \sum_{i=1}^{N} \frac{(y_i - \lambda(x_i; \vec{\theta}))^2}{\sigma_i^2}$$

Definition of least squares (LS) estimators

If the y_i follow a multivariate Gaussian, covariance matrix V,

$$g(\vec{y}; \vec{\lambda}, V) = \frac{1}{(2\pi)^{N/2}|V|^{1/2}} \exp\left[-\frac{1}{2}(\vec{y}-\vec{\lambda})^T V^{-1}(\vec{y}-\vec{\lambda})\right]$$

then the log-likelihood is

$$\log L(\vec{\theta}) = -\frac{1}{2}\sum_{i,j=1}^{N}(y_i - \lambda(x_i;\vec{\theta}))(V^{-1})_{ij}(y_j - \lambda(x_j;\vec{\theta})),$$

i.e. we should minimize

$$\chi^2(\vec{\theta}) = \sum_{i,j=1}^{N}(y_i - \lambda(x_i;\vec{\theta}))(V^{-1})_{ij}(y_j - \lambda(x_j;\vec{\theta}))$$

Its minimum defines the least squares (LS) estimators $\hat{\vec{\theta}}$, even when y_i not Gaussian. (In fact, y_i often Gaussian because central limit theorem leads to Gaussian measurement errors.)

C.F. Gauss, Theoria Motus Corporum Coelestium in Sectionibus Conicis Solem Ambentium, Hamburgi Sumtibus Frid. Perthes et H.Besser Liber II, Sectio II (1809);
C.F. Gauss, Theoria Combinationis Observationum Erroribus Minimis Obnoxiae, pars prior (15.2.1821) et pars posterior (2.2.1823), Commentationes Societatis Regiae Scientiarium Gottingensis Recectiores Vol. V (MDCCCXXIII).

Linear least squares fit

LS has particularly simple properties if $\lambda(x;\vec{\theta})$ linear in $\vec{\theta}$:

$$\lambda(x;\vec{\theta}) = \sum_{j=1}^{m} a_j(x)\theta_j$$

where $a_j(x)$ are any linearly independent functions of x.

→ $\hat{\vec{\theta}}$ have zero bias, minimum variance (Gauss–Markov theorem)

Matrix notation: let $A_{ij} = a_j(x_i)$,

$$\chi^2(\vec{\theta}) = (\vec{y}-\vec{\lambda})^T V^{-1} (\vec{y}-\vec{\lambda})$$

$$= (\vec{y}-A\vec{\theta})^T V^{-1} (\vec{y}-A\vec{\theta})$$

Set derivitives with respect to θ_i to zero,

$$\nabla\chi^2 = -2(A^T V^{-1}\vec{y} - A^T V^{-1} A\vec{\theta}) = 0$$

Solve to get the LS estimators,

$$\hat{\vec{\theta}} = (A^T V^{-1} A)^{-1} A^T V^{-1}\vec{y} \equiv B\,\vec{y}$$

N.B. estimators $\hat{\theta}_i$ are linear functions of the measurements y_i.

Variance of LS estimators

Error propagation (exact for linear problem) for $U_{ij} = \mathrm{cov}[\hat{\theta}_i, \hat{\theta}_j]$:

$$U = B\,V\,B^T = (A^T V^{-1} A)^{-1}$$

Equivalently, use

$$(U^{-1})_{ij} = \frac{1}{2}\left[\frac{\partial^2\chi^2}{\partial\theta_i\partial\theta_j}\right]_{\vec{\theta}=\hat{\vec{\theta}}}$$

→ coincides with RCF bound if y_i are Gaussian.

For $\lambda(x;\vec{\theta})$ linear in the parameters, $\chi^2(\vec{\theta})$ is quadratic,

$$\chi^2(\vec{\theta}) = \chi^2(\hat{\vec{\theta}}) + \frac{1}{2}\sum_{i,j=1}^{m}\left[\frac{\partial^2\chi^2}{\partial\theta_i\partial\theta_j}\right]_{\vec{\theta}=\hat{\vec{\theta}}}(\theta_i - \hat{\theta}_i)(\theta_j - \hat{\theta}_j)$$

→ variances from tangent planes to (hyper)ellipse,

$$\chi^2(\vec{\theta}) = \chi^2(\hat{\vec{\theta}}) + 1 = \chi^2_{\min} + 1$$

If $\lambda(x;\vec{\theta})$ not linear in $\vec{\theta}$, then expressions above not exact (but may still be good approximations).

Still interpret region $\chi^2(\vec{\theta}) \leq \chi^2_{\min} + 1$ as 'confidence region', having given probability of containing true $\vec{\theta}$ (more later).

N.B. formulae above don't depend on y_i being Gaussian, but in any case need $V_{ij} = \mathrm{cov}[y_i, y_j]$.

LS fit of a polynomial

Fit a polynomial: $\lambda(x;\theta_0,\ldots,\theta_m) = \sum_{j=0}^{m}\theta_j\,x^j$

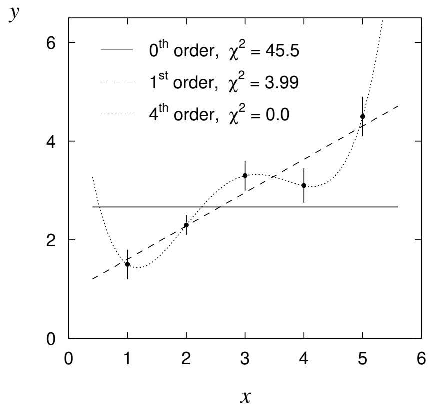
$a_j(x) = x^j$

Examples:

0th order (1 parameter)

1st order (2 parameters)

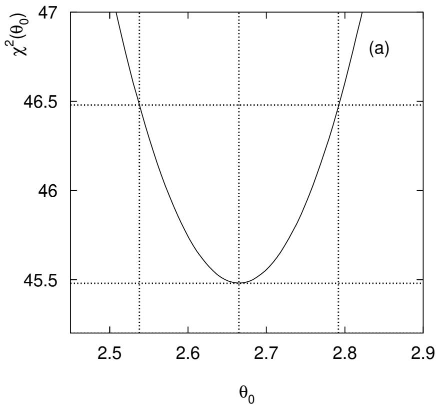
4th order (5 parameters)



1-parameter fit (i.e. horizontal line):

$\hat{\theta}_0 = 2.66 \pm 0.13$

$\chi^2_{\min} = 45.5$

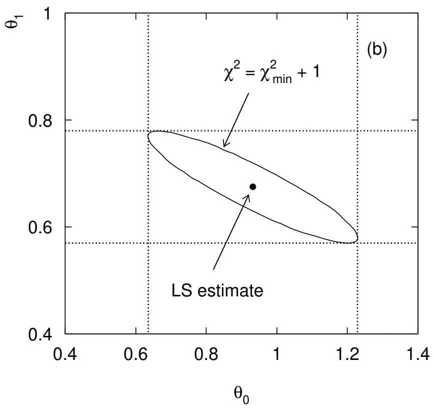


$\sigma_{\hat{\theta}_0}$ from $\chi^2(\hat{\theta}_0 \pm \sigma_{\hat{\theta}_0}) = \chi^2_{\min} + 1$.

Polynomial fit (continued)

2-parameter case (line with nonzero slope):

$$\hat{\theta}_0 = 0.93 \pm 0.30,$$
$$\hat{\theta}_1 = 0.68 \pm 0.10$$
$$\widehat{\mathrm{cov}}[\hat{\theta}_0, \hat{\theta}_1] = -0.028$$
$$r = -0.90$$
$$\chi^2 = 3.99$$



Tangent lines $\rightarrow$ $\sigma_{\hat{\theta}_0}$, $\sigma_{\hat{\theta}_1}$.

Angle of ellipse $\rightarrow$ correlation (same as for ML)

Could transform $(\hat{\theta}_0, \hat{\theta}_1) \rightarrow (\hat{\eta}_0, \hat{\eta}_1)$ such that $\mathrm{cov}[\hat{\eta}_0, \hat{\eta}_1] = 0$,

easier to work with uncorrelated estimators, but interpretation

of new parameters may not be obvious, cf. SDA Section 1.7.

5-parameter case:

curve goes through all points,

$\chi^2_{\mathrm{min}} = 0$,

(number of parameters = number of data points)

Value of χ^2_{min} reflects agreement between data and hypothesis,

$\rightarrow$ use as goodness-of-fit test statistic

Testing goodness-of-fit with LS

If: the y_i, $i = 1, \ldots, N$, are Gaussian (V_{ij} known),

the hypothesis $\lambda(x; \vec{\theta})$ is linear in θ_i, $i = 1, \ldots, m$, and

the form of the hypothesis $\lambda(x; \vec{\theta})$ is correct,

then χ^2_{min} follows chi-square pdf for $N - m$ degrees of freedom.

From this compute P-value,

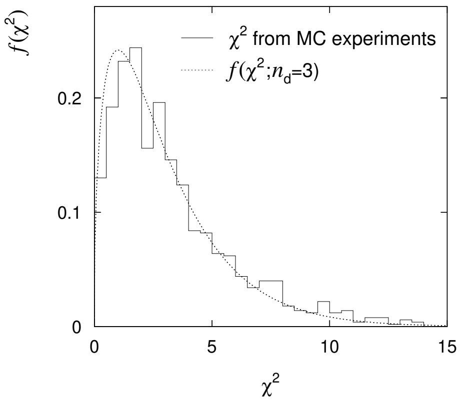
$$P = \int_{\chi^2_{\mathrm{min}}}^{\infty} f(z; n_{\mathrm{d}})\, dz$$

Consider e.g. 2-parameter fit:

$$\chi^2_{\mathrm{min}} = 3.99, \; N - m = 3 \rightarrow P = 0.263$$

i.e. repeat experiment many times, 26.3% will have higher χ^2_{min}.

1000 MC experiments:



For the horizontal line fit, we had

$$\chi^2_{\mathrm{min}} = 45.5, \; N - m = 4 \rightarrow P = 3.1 \times 10^{-9}$$

Goodness-of-fit vs. smallness-of-errors

Small statistical error does not mean a good fit (nor vice versa).

Curvature of χ^2 near its minimum $\rightarrow$ statistical errors ($\sigma_{\hat{\theta}}$)

Value of $\chi^2_{\min}$ $\rightarrow$ goodness-of-fit

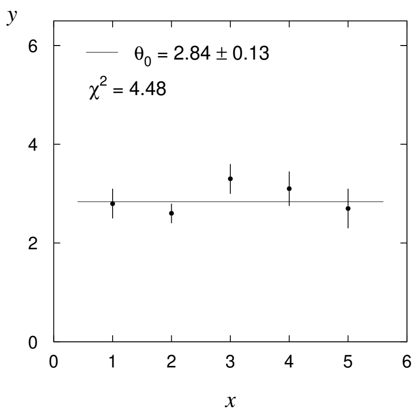
Horizontal line fit, move the data points, keep errors on points same:

$\hat{\theta}_0 = 2.84 \pm 0.13$

$\chi^2_{\min} = 4.48$

Variance same as before,

now $\chi^2_{\min}$ 'good'.



$\rightarrow$ $\chi^2(\theta_0)$ shifted down, same curvature as before.

Variance of estimator (statistical error) tells us:

if experiment repeated many times, how wide is the distribution of the estimates $\hat{\theta}$. (Doesn't tell us whether hypothesis correct.)

P-value tells us:

if hypothesis is correct and experiment repeated many times, what fraction will give equal or worse agreement between data and hypothesis according to the statistic $\chi^2_{\min}$.

Low P-value $\rightarrow$ hypothesis may be wrong $\rightarrow$ systematic error.

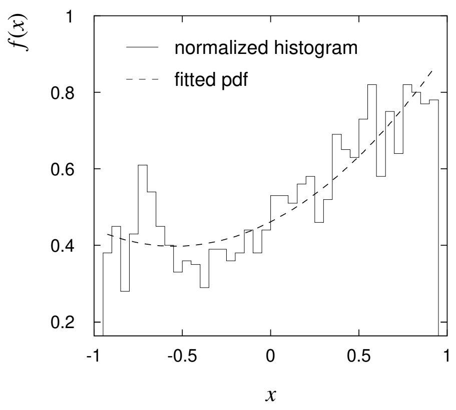
LS with binned data

Histogram:

N bins, n entries.

Hypothesized pdf:

$f(x;\vec{\theta})$



We have

$$y_i = \text{number of entries in bin } i,$$

$$\lambda_i(\vec{\theta}) = n \int_{x_i^{\min}}^{x_i^{\max}} f(x;\vec{\theta})dx = np_i(\vec{\theta})$$

LS fit: minimize

$$\chi^2(\vec{\theta}) = \sum_{i=1}^{N} \frac{(y_i - \lambda_i(\vec{\theta}))^2}{\sigma_i^2}$$

where $\sigma_i^2 = V[y_i]$, here not known a priori.

Treat the y_i as Poisson r.v.s, in place of true variance take either

$$\sigma_i^2 = \lambda_i(\vec{\theta}) \qquad \text{(LS method)}$$

$$\sigma_i^2 = y_i \qquad \text{(Modified LS method)}$$

MLS sometimes easier computationally, but $\chi^2_{\min}$ no longer follows chi-square pdf (or is undefined) if some bins have few (or no) entries.

Normalization with binned LS

Do not 'fit the normalization':

$$\lambda_i(\vec{\theta}, \nu) = \nu \int_{x_i^{\min}}^{x_i^{\max}} f(x; \vec{\theta}) dx = \nu p_i(\vec{\theta})$$

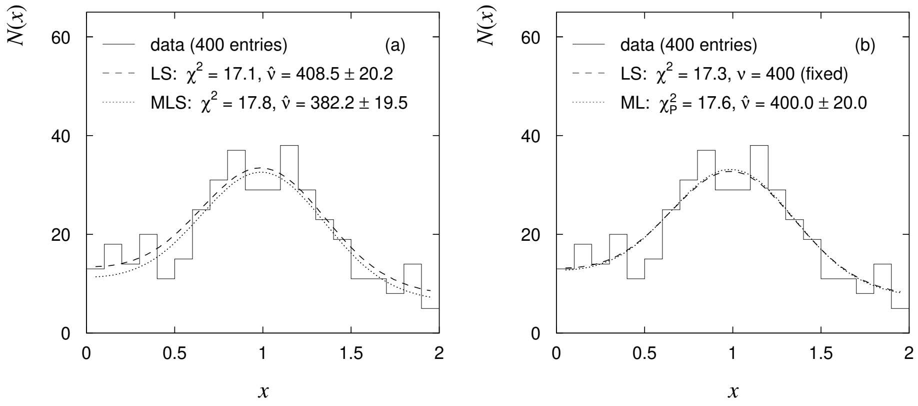
i.e. introduce adjustable ν, fit along with $\vec{\theta}$.

$\hat{\nu}$ is a bad estimator for n (which we know, anyway!)

$$\hat{\nu}_{\mathrm{LS}} = n + \frac{\chi^2_{\min}}{2}$$

$$\hat{\nu}_{\mathrm{MLS}} = n - \chi^2_{\min}$$

Example with $n = 400$ entries, $N = 20$ bins:



Expect $\chi^2_{\min}$ around $N - m$,

$\rightarrow$ relative error in $\hat{\nu}$ large when N large, n small

Either get n directly from data for LS (or better, use ML).

Combining measurements with LS

Use LS to obtain weighted average of N measurements of λ:

y_i = result of measurement i, $i = 1, \ldots, N$;

$\sigma_i^2 = V[y_i]$, assume known;

λ = true value (plays role of θ).

For uncorrelated y_i, minimize

$$\chi^2(\lambda) = \sum_{i=1}^{N} \frac{(y_i - \lambda)^2}{\sigma_i^2},$$

Set $\frac{\partial \chi^2}{\partial \lambda} = 0$ and solve,

$$\rightarrow \quad \hat{\lambda} = \frac{\Sigma_{i=1}^N y_i / \sigma_i^2}{\Sigma_{j=1}^N 1/\sigma_j^2}$$

$$V[\hat{\lambda}] = \frac{1}{\Sigma_{i=1}^N 1/\sigma_i^2}$$

If $\mathrm{cov}[y_i, y_j] = V_{ij}$, minimize

$$\chi^2(\lambda) = \sum_{i,j=1}^{N} (y_i - \lambda)(V^{-1})_{ij}(y_j - \lambda),$$

$$\rightarrow \quad \hat{\lambda} = \sum_{i=1}^{N} w_i y_i, \qquad w_i = \frac{\Sigma_{j=1}^N (V^{-1})_{ij}}{\Sigma_{k,l=1}^N (V^{-1})_{kl}}$$

$$V[\hat{\lambda}] = \sum_{i,j=1}^{N} w_i V_{ij} w_j$$

LS $\hat{\lambda}$ has zero bias, minimum variance (Gauss–Markov theorem).

Example of averaging two correlated measurements

Suppose we have y_1, y_2, and $V = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$

$$\rightarrow \quad \hat{\lambda} = w y_1 + (1-w) y_2, \quad w = \frac{\sigma_2^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2}$$

$$V[\hat{\lambda}] = \frac{(1-\rho^2)\sigma_1^2\sigma_2^2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} = \sigma^2$$

The increase in inverse variance due to 2nd measurement is

$$\frac{1}{\sigma^2} - \frac{1}{\sigma_1^2} = \frac{1}{1-\rho^2}\left(\frac{\rho}{\sigma_1} - \frac{1}{\sigma_2}\right)^2 > 0$$

$\rightarrow$ 2nd measurement can only help.

If $\rho > \sigma_1/\sigma_2$, $\rightarrow$ $w < 0$,

$\rightarrow$ weighted average is not between y_1 and y_2 (!?)

Cannot happen if correlation due to common data, but possible for shared random effect; very unreliable if e.g. ρ, σ_1, σ_2 incorrect.

See example in SDA Section 7.6.1 with two measurements at same temperature using two rulers, different thermal expansion coefficients:

average is outside the two measurements; used to improve estimate of temperature.

Lecture 8 summary

The method of least squares

1. **Connection with maximum likelihood:** ML and LS same for Gaussian y_i.
2. **Linear LS problem:** if $\lambda(x;\vec{\theta})$ linear in the parameters, LS can be solved by matrix inversion; estimators are linear functions of the measurements y_i.
3. **LS fit of a polynomial:** an example of the linear problem. $\chi^2_{\min}$ gets smaller when using more parameters, goes to zero for $N = m$.
4. **Testing goodness-of-fit with LS:** use $\chi^2_{\min}$ as goodness-of-fit statistic, follows chi-square pdf for $N - m$ degrees of freedom.
5. **LS with binned data:** treat y_i as Poisson,

   LS: $\sigma_i^2 = \lambda_i(\vec{\theta})$,

   MLS: $\sigma_i^2 = y_i$

   Do not fit the normalization (get n from the data).
6. **Combining measurements with LS:** LS gives zero bias, minimum variance. Additional measurements can only help. For large correlations, weights can be negative.