

Point Estimation

The goal of Point Estimation is to find **the point in μ -space** which gives **the “best” estimate** (measurement) of the parameter μ .

We assume, as always, $P(\text{data}|\text{hypothesis}) = P(X|\mu)$ known.

What we mean by the “best” estimate depends very much on whether we will use a Frequentist or Bayesian method.

Historically, the Bayesian was the first method, so we start there.

Bayes' Theorem for Parameter Estimation

For estimation of the parameter μ , we can rewrite Bayes' Theorem:

$$P(\mu|\text{data}) = \frac{P(\text{data}|\mu)P(\mu)}{P(\text{data})}$$

Evaluating $P(\text{data}|\mu)$ at the observed data is the likelihood function, so we have:

$$P(\mu|\text{data}) = \frac{\mathcal{L}(\mu)P(\mu)}{P(\text{data})}$$

which is a **probability density function** in the unknown μ .

$P(\text{data})$ is just a constant, which can be determined from the normalization condition: $\int_{\Omega} P(\mu|\text{data}) = 1$

Note that the above cannot be Frequentist probabilities, because **hyp** and μ are not random variables.

They determine the **degree of belief** in different values of μ .

Priors and Posteriors

Assigning names to the different factors, we get:

$$\text{Posterior pdf}(\mu) = \frac{\mathcal{L}(\mu) \times \text{Prior pdf}(\mu)}{\text{normalization factor}}$$

The **Prior pdf** represents your belief about μ before you do any experiments. If you already have some experimental knowledge about μ (for example from a previous experiment), you can use the posterior pdf from the previous expt. as the prior for the new one. But this implies that somewhere in the beginning there was a prior which contained no experimental evidence [Glen Cowan calls this the **Ur-prior**].

In the true Bayesian spirit, the **posterior density** represents all our knowledge and belief about μ , so there is no need to process this pdf any further.

Point Estimation - from Bayesian to Frequentist

Up to the early 1900's, the only statistical theory was Bayesian.

In fact, frequentist methods were already being used: Linear least-squares fitting of data had been in use for many years, although its statistical properties were unknown.

And in 1900, **Karl Pearson** published the **Chi-square test** to be treated later under *goodness-of-fit*.

About the same time, another English biologist, **R. A. Fisher**, was one of several people looking for a statistical theory that would not require as input **prior belief** and would not be based on subjective probabilities.

He succeeded in making a **frequentist theory of point estimation**, (but was unable to produce an acceptable theory of **interval estimation**).

Point Estimation - Frequentist

An **Estimator** \mathcal{E}_θ is a function of the data X which can be used to estimate (measure) the unknown parameter θ to produce the **estimate** $\hat{\theta}$.

$$\hat{\theta} = \mathcal{E}_\theta(X)$$

The goal:

Find that function \mathcal{E}_θ which gives **estimates** $\hat{\theta}$ **closest to the true value of** θ .

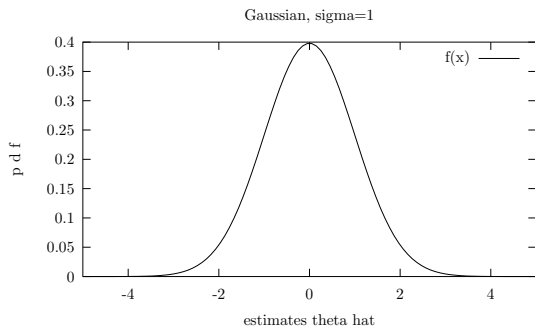
As usual, we know $P(X|\theta)$

and because the estimate is a function of the data, we also know the distribution of $\hat{\theta}$, for any given value of θ :

$$P(\hat{\theta}|\theta) = \int_{\mathcal{X}} \mathcal{E}_\theta(X) P(X|\theta) dX$$

Frequentist Estimates

For our trial estimator \mathcal{E}_θ , assuming $\theta = 0$, the distribution of estimates $\hat{\theta}$ might look something like this:



Now we can see whether this estimator has the desired properties. Is it (1) **consistent**, (2) **unbiased**, (3) **efficient**, and (4) **robust**?

Consistency

Let \mathcal{E}_θ be an estimator producing estimates $\hat{\theta}_n$, where n is the number of observations entering into the estimate.

Given any $\varepsilon > 0$ and any $\eta > 0$, \mathcal{E}_θ is a **consistent estimator** of θ if an N exists such that

$$P(|\hat{\theta}_n - \theta_0| > \varepsilon) < \eta$$

for all $n > N$, where θ_0 is the assumed true value.

That is, if \mathcal{E}_θ is a **consistent estimator** of θ , the estimates $\hat{\theta}_n$ converge (in probability) to the true value of θ .

Since all reasonable Frequentist estimators are consistent, I thought this property was only of theoretical interest, until I discovered that Bayesian estimators are not in general consistent in many dimensions.

Bias

We define the **bias b of the estimate $\hat{\theta}$** as the difference between the expectation of $\hat{\theta}$ and the true value θ_0 ,

$$b_N(\hat{\theta}) = E(\hat{\theta}) - \theta_0 = E(\hat{\theta} - \theta_0).$$

Thus, an estimator is **unbiased** if, for all N and θ_0 ,

$$b_N(\hat{\theta}) = 0$$

or

$$E(\hat{\theta}) = \theta_0.$$

Bias vs Consistency

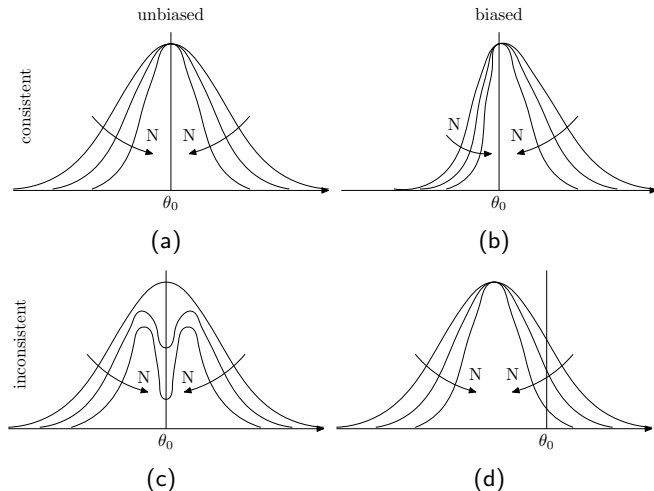


Figure: examples of distributions of estimates with different properties. The arrows show increasing amount of data.

Efficiency

Among those estimators that are consistent and unbiased, we clearly want the one whose estimates have the smallest spread around the true value, that is, estimators with a small **variance**.

We define the **efficiency** of an estimator in terms of the variance of its estimates $V(\hat{\theta})$:

$$\text{Efficiency} = \frac{V_{\min}}{V(\hat{\theta})}$$

where V_{\min} is the smallest variance of any estimator.

The above definition is possible because, as we shall see, V_{\min} is given by the **Cramér-Rao lower bound**.

Fisher Information

Let the pdf of the data X be denoted by f or by L :

$$P(\text{data}|\text{hypothesis}) = f(X|\theta) = L(X|\theta)$$

depending on whether we are primarily interested in the dependence on X or θ .

The amount of information given by an observation X about the parameter θ is defined by the following expression (if it exists)

$$\begin{aligned} I_X(\theta) &= E \left[\left(\frac{\partial \ln L(X|\theta)}{\partial \theta} \right)^2 \right] \\ &= \int_{\Omega_\theta} \left(\frac{\partial \ln L(X|\theta)}{\partial \theta} \right)^2 L(X|\theta) dX. \end{aligned}$$

Fisher Information cont.

If θ has k dimensions, the definition becomes

$$\begin{aligned} [\mathcal{L}_X(\theta)]_{ij} &= E \left[\frac{\partial \ln L(X|\theta)}{\partial \theta_i} \cdot \frac{\partial \ln L(X|\theta)}{\partial \theta_j} \right] \\ &= \int_{\Omega_\theta} \left[\frac{\partial \ln L(X|\theta)}{\partial \theta_i} \cdot \frac{\partial \ln L(X|\theta)}{\partial \theta_j} \right] L(X|\theta) dX. \end{aligned}$$

Thus, in general, $\mathcal{L}_X(\theta)$ is a $k \times k$ matrix. Assuming certain regularity conditions, the same matrix can be expressed as the expectation of the second derivative matrix [see next slide](#):

$$[\mathcal{L}_X(\theta)]_{ij} = -E \left[\frac{\partial^2}{\partial \theta_i \partial \theta_j} \ln L(X|\theta) \right].$$

from $E(\partial \ln L)^2$ to $E(\partial^2 \ln L)$

Since $L(x_1, x_2 \dots | \theta) = \prod_i f(x_i | \theta)$ is the joint density function of the data, it must be normalized:

$$\int_{\Omega} L dX = 1, \quad \text{so} \quad \int_{\Omega} \frac{\partial L}{\partial \theta} dX = 0$$

Multiply and divide by L:

$$\int_{\Omega} \left(\frac{1}{L} \frac{\partial L}{\partial \theta} \right) L dX = E \left(\frac{\partial \ln L}{\partial \theta} \right) = 0$$

Differentiate again, and again move ∂ into the \int :

$$\int_{\Omega} \left\{ \left(\frac{1}{L} \frac{\partial L}{\partial \theta} \right) \frac{\partial L}{\partial \theta} + L \frac{\partial}{\partial \theta} \left(\frac{1}{L} \frac{\partial L}{\partial \theta} \right) \right\} dX = 0$$

$$E \left[\left(\frac{\partial \ln L}{\partial \theta} \right)^2 \right] = -E \left(\frac{\partial^2 \ln L}{\partial^2 \theta} \right)$$

Fisher Information cont.

So the **Fisher information** in the sample X about the parameter(s) θ is

$$[I_X(\theta)]_{ij} = -E \left[\frac{\partial^2}{\partial \theta_i \partial \theta_j} \ln L(X|\theta) \right].$$

It can be seen that $I_X(\theta)$ has the **additive property**: If I_N is the information in N events, then $I_N(\theta) = NI_1(\theta)$.

We will also see that **information** about θ is related to the **minimum variance** possible for an estimator of θ .

But first we introduce the concept of Sufficient Statistics

Sufficiency

Any function of the data is called a **statistic**.

A **sufficient statistic for θ** is a function of the data that contains all the information about θ .

A statistic $T(X)$ is sufficient for θ if the conditional density function for X given T , $f(X|T)$ is independent of θ .

Sufficient statistics are clearly important for **data reduction**.

Cramér-Rao Inequality

Let the estimator $\hat{\theta}$ be an unbiased estimator of θ with sampling distribution $q(\hat{\theta}|\theta)$.

Then the variance of the sampling distribution,

$$V(\hat{\theta}) = \int [\hat{\theta} - E(\hat{\theta})]^2 q(\hat{\theta}|\theta) d\hat{\theta},$$

is related to the information by the **Cramér-Rao inequality**:

$$V(\hat{\theta}) \geq \frac{1}{I_{\hat{\theta}}} = \frac{1}{E \left[\left(\frac{\partial \ln L}{\partial \theta} \right)^2 \right]}.$$

The Usual Estimators

The most common general-purpose estimators are:

- ▶ **The method of moments** is based on approximating $f(X|\theta)$ by its first few moments. It is surprisingly efficient for an approximate method, but will not be treated here.
- ▶ **Maximum likelihood** is the most important method, mostly because it can be shown to be **asymptotically efficient**.
- ▶ **Least squares** is **asymptotically efficient** for fitting data in histograms, and is generally easier to apply than M.L.

Maximum Likelihood

The likelihood of a set of N independent observations \mathbf{X} is

$$L(\mathbf{X}|\theta) = \prod_{i=1}^N f(X_i, \theta),$$

where $f(X, \theta)$ is the p.d.f. of any observation X .

The **maximum likelihood estimate** of the parameter θ is that value $\hat{\theta}$ for which $L(\mathbf{X}|\theta)$ has its maximum, given the particular observations \mathbf{X} .

Note that maximizing $\ln L$ or L gives the same result.

The **likelihood equation** is

$$\frac{\partial}{\partial \theta} \sum_{i=1}^N \ln f(X_i, \theta) = \frac{\partial}{\partial \theta} \ln L(\mathbf{X}, \theta) = 0.$$

since that is the analytic way to find the maximum, but in practice we will usually find the maximum numerically.

Asymptotic Properties of Maximum Likelihood

Asymptotically (for very large data samples), the M. L. estimator has optimal properties:

- ▶ It is **consistent**.
- ▶ It is **efficient**, the variance $V(\hat{\theta})$ being given by the Cramer–Rao lower bound

$$V(\hat{\theta}) \xrightarrow{N \rightarrow \infty} \left\{ E \left[\left(\frac{\partial \ln L}{\partial \theta} \right)^2 \right] \right\}^{-1}.$$

- ▶ The estimates $\hat{\theta}$ are **Normally distributed**.
- ▶ Since it is consistent, it is asymptotically **unbiased**.

Asymptotic Properties of Maximum Likelihood 2

If the range of the data is independent of the parameters θ , then the variance $V(\hat{\theta})$ may be estimated by

$$\hat{V}(\hat{\theta}) = \left\{ \left(- \frac{\partial^2 \ln L}{\partial \theta^2} \right) \Big|_{\theta=\hat{\theta}} \right\}^{-1}.$$

The estimate $\sqrt{N}(\hat{\theta} - \theta)$ is distributed as $N[0, I_1^{-1}(\theta)]$.

(Estimates are asymptotically Gaussian-distributed.)

We will give an example where the range of the data depends on the parameter, and the above properties do not hold..

Finite Sample Properties of Maximum Likelihood

- ▶ For finite samples, M.L. estimates are efficient only when there exist sufficient statistics for the parameter(s) being evaluated, and that can be shown only for the exponential family, consistent with the **Darmois Theorem**.
- ▶ Although the estimates are in general **biased**, they have a more important property, **invariance**, which is incompatible with unbiasedness because the definition of bias is not invariant.

Least Squares

Consider a set of observations Y_1, \dots, Y_N from a distribution with expectations $E(Y_i, \boldsymbol{\theta})$ and covariance matrix \mathcal{V} . The $\boldsymbol{\theta}$ are unknown parameters and the $E(Y_i, \boldsymbol{\theta})$ and $V_{ij}(\boldsymbol{\theta})$ are known functions of $\boldsymbol{\theta}$.

In the method of least squares the estimates of the θ_k are those values $\hat{\theta}_k$ which minimize

$$\begin{aligned} Q^2 &= \sum_{i=1}^N \sum_{j=1}^N [Y_i - E(Y_i, \boldsymbol{\theta})](\mathcal{V}^{-1})_{ij} [Y_j - E(Y_j, \boldsymbol{\theta})] \\ &= [\mathbf{Y} - E(\mathbf{Y}, \boldsymbol{\theta})]^T \mathcal{V}^{-1} [\mathbf{Y} - E(\mathbf{Y}, \boldsymbol{\theta})]. \end{aligned}$$

Least Squares 2

When the observations Y_i are independent, it follows that they are uncorrelated, and the covariance matrix is diagonal, with elements

$$V_{ii} = \sigma_i^2(\boldsymbol{\theta}).$$

The covariance form then simplifies to the familiar sum of squares

$$Q^2 = \sum_{i=1}^N \frac{[Y_i - E(Y_i, \boldsymbol{\theta})]^2}{\sigma_i^2(\boldsymbol{\theta})}$$

The $\hat{\boldsymbol{\theta}}$ are found by solving the **Normal equations**

$$\partial Q^2 / \partial \boldsymbol{\theta} = 0,$$

Linear Least Squares

The method of **linear least squares** is applicable when the variances σ_i^2 are independent of the r parameters $\boldsymbol{\theta} = (\theta_1, \dots, \theta_r)$, and the expectations $E(Y_i, \boldsymbol{\theta})$ are linear in the θ_j 's,

$$E(Y_i, \boldsymbol{\theta}) = \sum_{j=1}^r a_{ij} \theta_j, \quad i = 1, \dots, N$$

or in matrix notation

$$E(\mathbf{Y}, \boldsymbol{\theta}) = \mathcal{A} \boldsymbol{\theta}$$

The elements a_{ij} of the *design matrix* \mathcal{A} are given by a model.

In the linear case, the solution of the **Normal equations** is

$$\hat{\boldsymbol{\theta}} = (\mathcal{A}^T \mathcal{V}^{-1} \mathcal{A})^{-1} \mathcal{A}^T \mathcal{V}^{-1} \mathbf{Y}.$$

Linear Least Squares cont.

Since the linear least squares solution is found by matrix inversion and multiplication (no minimization needed), one often solves the **non-linear problem** by **linearization**, setting:

$$a_{ij} = \frac{\partial E(Y_i, \theta)}{\partial \theta_j}$$

Example of linear least squares: fitting a curve to a polynomial.

$$Y_i = Y(X_i) = \theta_0 + \theta_1 X_i + \theta_2 X_i^2 + \theta_3 X_i^3$$

is clearly of the linear form. To find the matrix A one only needs to evaluate the $(j-1)^{\text{th}}$ power of X_i .

Solving the **Normal equations** $\partial Q^2 / \partial \theta = 0$, we find:

$$\hat{\theta} = (A^T V^{-1} A)^{-1} A^T V^{-1} \mathbf{Y}.$$

which is exact and unique as long as $A^T V^{-1} A$ is non-singular.

Least Squares

For fitting data in histograms, the **asymptotic properties of least squares** are the same as for maximum likelihood, and in fact the two methods are often identical. When they are different, it is believed that M.L. generally approaches the asymptotic limit faster than L.S.

The biggest difference is largely practical.

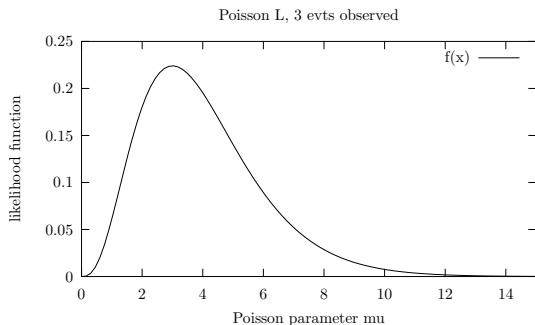
If the data are already grouped into bins or points, L.S. is more convenient and there is no advantage in using M.L.

The subject of M.L. and L.S. fitting will be treated in more detail in the second half of the course.

Point Estimation: Example: Poisson data

Example: In a Poisson process, we observe 3 events.

$$\mathcal{L}(\mu) = P(3|\mu) = \frac{e^{-\mu} \mu^3}{3!}$$



The peak in the likelihood occurs at $\mu = 3$.

Generalizing from 3 to n , we get the expected result:

with n events observed, $\hat{\mu} = n$

Example: Weighted Average

Suppose we have Normally-distributed observations X_i of a quantity μ , each X_i being distributed with standard deviation σ_i :

$$f(X_i|\mu) = N(\mu, \sigma_i^2) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp \left[-\frac{1}{2} \frac{(X_i - \mu)^2}{\sigma_i^2} \right].$$

We wish to use this data to estimate μ . The **likelihood function** is the product of the $f(X_i|\mu)$, and its logarithm is:

$$\ln \mathcal{L}(\mu) = k - \sum_i \frac{1}{2} \frac{(X_i - \mu)^2}{\sigma_i^2}$$

where k is a constant. It is clear that in this case,

maximizing the log likelihood is equivalent to **minimizing χ^2** .

In both cases, the solution is the familiar **weighted average**:

$$\hat{\mu} = \frac{\sum_i \frac{X_i}{\sigma_i^2}}{\sum_i \frac{1}{\sigma_i^2}}$$

Example: A Poor M. L. Estimator

Suppose that one observes N events X_i chosen randomly from a uniform distribution between 0 and θ , where the upper bound θ is the unknown parameter.

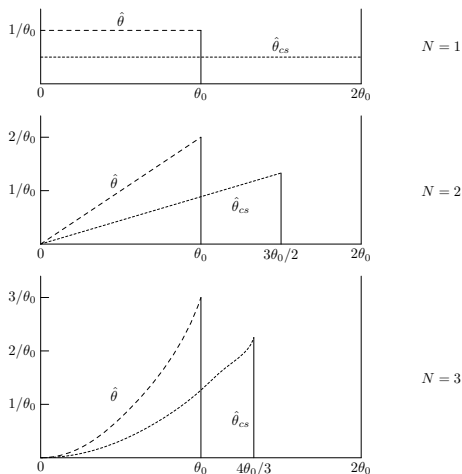
This is a case where **the range of the data depends on the value of the parameter θ .**

Since $\theta \geq X_i$ for all i , the likelihood function $L = \theta^{-N}$ will have its maximum at $\hat{\theta} = X_{\max}$, where X_{\max} is the largest observed value of X . It is clear that this estimator (almost) always gives a result which is too small, and the obvious correction is to use the common-sense estimate:

$$\hat{\theta}_{\text{cs}} = X_{\max} + \frac{X_{\max}}{N}.$$

This estimate in fact turns out to be unbiased, as can easily be verified.

Example: A Poor M. L. Estimator cont.



Distribution of maximum-likelihood estimates $\hat{\theta}$ and common-sense estimates $\hat{\theta}_{CS}$ for $N = 1, 2, 3$.

Robustness

Suppose we wish to estimate of the centre of an unknown, symmetric distribution. The centre of a distribution is defined by a **location parameter**. Some examples are:

- ▶ The **mean** is the expectation of the variable X .
- ▶ The **median** is that value X for which the cumulative distribution has $F(X) = 0.5$.
- ▶ The **mode** is that value of X for which the p.d.f. has a maximum.
- ▶ The **midrange** is defined when the possible values of X are limited to the range $[X_{\min}, X_{\max}]$. Then the *midrange* is $(X_{\min} + X_{\max})/2$.

Robustness cont.

For any particular sample of (finite) data X_i , we can define:

- ▶ The **sample mean** is the mean or average of the X_i .
- ▶ The **sample median** is the value X such that half the X_i lie above it and half below. If the number of data values is odd, it is the central value. If the number is even, it is usually taken as halfway between the two central values.
- ▶ The **sample mode** is the value of X halfway between the two nearest values of X_i .
- ▶ The **sample midrange** is halfway between the smallest and largest values of X_i , that is $(X_{i \min} + X_{i \max})/2$.

Robustness 3

The sample mean is the most obvious and most often used estimator of location, because

- ▶ it is consistent whenever the variance of the underlying distribution is finite (law of large numbers);
- ▶ it is optimal (minimum variance, unbiased) when the underlying distribution is Normal.

However, if the distribution of X is not Normal, the sample mean is not the best estimator of the mean of the distribution, even when the mean of the distribution exists. Below we list the best estimator of location for some important distributions:

Distribution	Minimum-variance location estimator
Normal	sample mean
Uniform	midrange (mean of extreme values)
Cauchy	maximum-likelihood estimate
Double-exponential	median (middle value)

Robustness 4

A **robust estimator** is one which, although not optimally efficient for any one distribution, has a high efficiency over a broad range of distributions. Let us define:

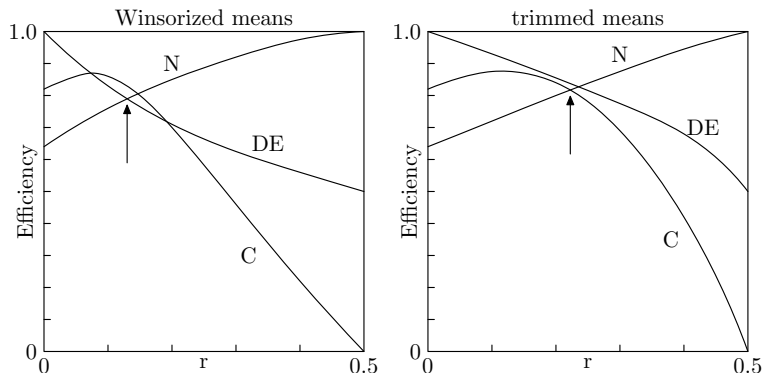
- ▶ **The trimmed mean** of the total of N observations: remove the $n/2$ highest values and the $n/2$ lowest values, and compute the mean of the remaining $N - n$ observations.
- ▶ **The Winsorized mean** of the total of N observations: replace the $n/2$ highest values by the highest remaining value, and the $n/2$ lowest by the lowest remaining value, and compute the mean of the new sample of N values.

For both estimators there is one free parameter, usually taken as half the fraction of remaining (unchanged, or not rejected) values,

$$r = \frac{N - n}{2N}.$$

Note that for $r = 0.5$, both estimators are in fact the sample mean, and as $r \rightarrow 0$, both become equivalent to the sample median.

Robustness 5



Asymptotic efficiencies of trimmed and Winsorized means for Normal (N), double-exponential (DE) and Cauchy (C) distributions. Arrows indicate minimax point for optimum robustness.

N-dependence of errors

Physicists distinguish between two sources of error:
statistical errors and **systematic errors**.

Statisticians distinguish two different sources of error:
 The **bias** and **variance** of an estimator.

We will distinguish three different sources of experimental error, each with its own dependence on the number of observations n .

- ▶ **The systematic error** usually does not decrease with n .
- ▶ **The bias** of an asymptotically unbiased estimator typically decreases like n^{-1} .
- ▶ **The statistical error**, or **square root of the variance** of an estimator, typically decreases like $n^{-1/2}$, but there are exceptions: (e.g. **midrange in slide 46**.)

Why least squares?

1. When the data are **Gaussian-distributed** :
Maximum Likelihood reduces to **Least Squares**.

But Least Squares is older than M.L. So why was it used? Probably because:

- ▶ In the **Decision-Theoretic Approach**, it follows from a **quadratic penalty or cost function**.
 - ▶ When the model is **linear**, the solution is a linear function of the data.
2. So what happens if we try minimizing the sums of **different powers** of the residuals?

Alternatives to Least Squares

Should one sometimes use least cubes, least absolute values, etc.?

We call a_p the L_p estimate of location if a_p minimizes the quantity

$$L_p(a) = \sum_{i=1}^N |X_i - a|^p.$$

For all $p \geq 1$, the L_p estimate is well-defined, and the properties of these estimates have been studied [[Rice and White, 1964](#)].

1. For $p = 1$, a_p is the **sample median**.
2. For $p = 2$, a_p is the **sample mean**, the least-squares estimator.
3. For $p = \infty$, a_p is the **sample midrange**, the average of the lowest and highest values. L_∞ is the **Chebyshev Norm**.
4. As $p \rightarrow -\infty$, a_p tends to the **sample mode**, the point of highest density, corresponding to the maximum of the pdf.

So small (or negative) values of p give more weight to points near the middle of the distribution,

and large values give more weight to the tails.

Why least squares?

Asymptotic variances of L_p location estimates.
for some symmetric distributions

Distribution	L_1 (median)	L_2 (mean)	L_∞ (midrange)
Uniform	$1/4N$	$1/12N$	$1/(2N^2 + 6N + 4)$
Triangular		$1/6N$	$(4 - \pi)/4N$
Normal	$\pi/2N$	$1/N$	$\pi^2/12 \log N$
Double-exponential	$1/2N$	$2/N$	$\pi^2/12$
Cauchy	$\pi^2/4N$	∞	∞

This means that when fitting a set of points to a hypothesis (for example, fitting a track to measurements in a detector) the usual **least-squares** estimator, based on the L_2 Norm, is optimal only if the measurements are **Normally distributed**. For some detectors, another L_p norm may be more efficient.

Examples where Least Squares is not Optimal

1. Fitting Points to a curve

when the point measurements are **not Normally** distributed.

When the distribution of measurements has **longer tails than a Gaussian**, use the L_p norm with $p < 2$.

The opposite extreme (distributions with **no tails at all**) may be attained with some detectors based on discrete elements (strips or wires) such that a **hit defines a window** through which the track must pass.

In this case, the Chebyshev Norm may provide much superior accuracy compared with least squares.

See [F. James, *Fitting Tracks in Wire Chambers using the Chebyshev Norm instead of Least Squares*, NIM 211\(1983\)145](#)

2nd Example where Least Squares is not Optimal

2. Fitting data to a Histogram

when there are not many events in some bins.

Then the Poisson distribution of events in each bin is **not** approximately Gaussian, and it is better to use the **binned likelihood**.

See Baker and Cousins, *Clarification of the Use of Chi-square and Likelihood Functions in Fits to Histograms* NIM 221 (1984) 437

2nd Example where Least Squares is not Optimal

from: Baker and Cousins, *Clarification of the Use of Chi-square and Likelihood Functions in Fits to Histograms* NIM 221 (1984) 437

The likelihood function for the Poisson-distributed histogram contents is

$$L(\theta) = \prod_i e^{-\mu_i(\theta)} \mu_i^{n_i}(\theta) / n_i!$$

where $\mu_i(\theta)$ is the content of the i^{th} bin predicted by the model, and n_i is the observed contents of the bin.

It is convenient to work with the likelihood ratio λ which is the above likelihood divided by the likelihood for data without errors. Then the quantity $-2 \ln \lambda$ asymptotically obeys a Chi-square distribution, and the quantity to be minimized reduces to

$$\chi_\lambda^2 = -2 \ln \lambda = 2 \sum_i [\mu_i(\theta) - n_i + n_i \ln(n_i / \mu_i(\theta))]$$