Statistics course outline

Lecture 1

1. **Probability**
2. **Random variables, probability densities, etc.**
3. **Brief catalogue of probability densities**
4. **The Monte Carlo method**

Lecture 2

1. **Statistical tests**
2. **Fisher discriminants, neural networks, etc.**
3. **Goodness-of-fit tests**
4. **The significance of a signal**
5. **Introduction to parameter estimation**

Lecture 3

1. **The method of maximum likelihood (ML)**
2. **Variance of ML estimators**
3. **The method of least squares (LS)**
4. **Interval estimation, setting limits**

Hypotheses, test statistics

Suppose the result of a measurement is $\vec{x} = (x_1, \ldots, x_n)$

e.g. events from e^+e^- collisions; for each event measure

x_1 = number of charged particles produced

x_2 = mean $p_\perp$ of particles

x_3 = number of 'jets' (according to some algorithm)

$x_4 = \ldots$

$\vec{x}$ follows some joint pdf in an n-dimensional space, which depen

on the type of event produced, i.e. $e^+e^- \rightarrow q\bar{q}$, $e^+e^- \rightarrow$ WW, etc

That is, the joint pdf $f(\vec{x})$ is specified by a certain

HYPOTHESIS

i.e. predicted probability densities $f(\vec{x}|H_0)$, $f(\vec{x}|H_1)$, etc.

(Note sloppy but traditional notation: usually H_0, H_1, …not r.v

Simple hypothesis: $f(\vec{x})$ completely specified,

Composite hypothesis: form of $f(\vec{x};\theta)$ given, parameter θ unkn

Usually awkward to work with multidimensional $\vec{x}$,

⇒ construct test statistic of lower dimension (e.g. scalar), $t(\vec{x})$:

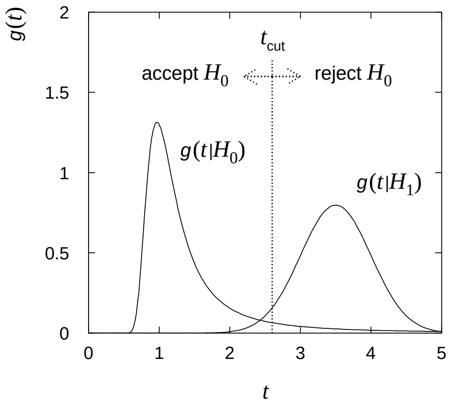
compactify data,

try not to lose ability to discriminate bewteen hypotheses.

The statistic t then has pdfs $g(t|H_0)$, $g(t|H_1)$, …

Critical region, errors of 1st and 2nd kind

Consider a test statistic t following $g(t|H_0)$, $g(t|H_1)$, . . .



Define a critical region where t is not likely to occur if H_0 is true,

e.g. for the case above, $t \geq t_{\rm cut}$.

If observed value $t_{\rm obs}$ is in critical region, reject H_0, otherwise 'accept'.

Probability to reject H_0 if it is true (error of 1st kind):

$$\alpha = \int_{t_{\rm cut}}^{\infty} g(t|H_0)\, dt \qquad \text{(significance level)}$$

Probability to accept H_0 if H_1 is true (error of 2nd kind):

$$\beta = \int_{-\infty}^{t_{\rm cut}} g(t|H_1)\, dt \qquad (1-\beta = \text{power})$$

An example with particle selection

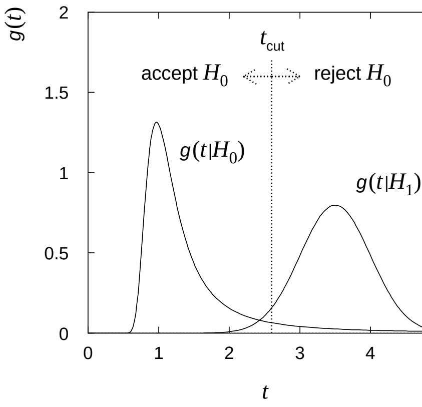
Suppose we obtain n energy loss measurements for a particle in

drift chamber, construct t = truncated mean of the measuremen

and suppose we know the particles are either electrons or pions:

H_0 = electron (signal)

H_1 = pion (background)



Select electrons by requiring $t < t_{\rm cut}$. The selection efficiencies

$$\varepsilon_{\rm e} = \int_{-\infty}^{t_{\rm cut}} g(t|{\rm e})dt = 1-\alpha$$

$$\varepsilon_{\pi} = \int_{-\infty}^{t_{\rm cut}} g(t|\pi)dt = \beta$$

Loose cut: most e accepted, lots of π background

Tight cut: low signal efficiency, pure sample

Fractions of e, π may be unknown; t follows

$$f(t;a_{\rm e}) = a_{\rm e}g(t|e) + (1-a_{\rm e})g(t|\pi)$$

→ estimate $a_{\rm e}$ (for now assume $a_{\rm e}$, $a_{\pi} = 1 - a_{\rm e}$ known)

Purity of selected sample

For a measured value t, what is the probability to be e/π?

$$h(\mathrm{e}|t) = \frac{a_{\mathrm{e}}\, g(t|\mathrm{e})}{a_{\mathrm{e}}\, g(t|\mathrm{e}) \, + \, a_{\pi}\, g(t|\pi)}$$

(Bayes' theorem)

$$h(\pi|t) = \frac{a_{\pi}\, g(t|\pi)}{a_{\mathrm{e}}\, g(t|\mathrm{e}) \, + \, a_{\pi}\, g(t|\pi)}$$

Bayesian: degree of belief that this particle is e or π

Frequentist: fraction of particles at given t which are e/π

→ here both approaches make sense

Often want purity of selected sample:

$$p_{\mathrm{e}} = P(\,\mathrm{e}\,|t < t_{\mathrm{cut}})$$

$$= \frac{\text{number of electrons with } t < t_{\mathrm{cut}}}{\text{number of all particles with } t < t_{\mathrm{cut}}}$$

$$= \frac{\int_{-\infty}^{t_{\mathrm{cut}}} a_{\mathrm{e}} g(t|\mathrm{e}) dt}{\int_{-\infty}^{t_{\mathrm{cut}}} (a_{\mathrm{e}} g(t|\mathrm{e}) + (1 - a_{\mathrm{e}}) g(t|\pi)) dt}$$

$$= \frac{\int_{-\infty}^{t_{\mathrm{cut}}} h(\mathrm{e}|t)\, f(t)\, dt}{\int_{-\infty}^{t_{\mathrm{cut}}} f(t)\, dt}$$

$$= \text{electron probability averaged over interval } (-\infty, t_{\mathrm{cut}}]$$

The Neyman–Pearson lemma

Consider a multidimensional test statistic $\vec{t} = (t_1, \ldots, t_m)$;
hypotheses H_0 ('signal') and H_1 ('background').
What is the optimal choice of the critical region (i.e. cuts)?

The Neyman–Pearson lemma states: to get the highest purity for a given efficiency, (i.e. highest power for a given significance level choose the acceptance region such that

$$\frac{g(\vec{t}|H_0)}{g(\vec{t}|H_1)} > c,$$

where c = constant which determines the efficiency.

(For a proof see Brandt Chapter 8.) Value of c left open; choose this depending on what efficiency you want.

Equivalently, the optimal scalar test statistic is

$$r \, = \, \frac{g(\vec{t}|H_0)}{g(\vec{t}|H_1)},$$

called the likelihood ratio for simple hypotheses H_0 and H_1.
Requiring $r > c$ gives maximum purity for a given efficiency.
N.B. any monotonic function of r is just as good.

Constructing a test statistic

Example: $H_0 = \mathrm{e}^+\mathrm{e}^- \to \mathrm{WW} \to$ hadrons (usually four jets)

$H_1 = \mathrm{e}^+\mathrm{e}^- \to q\bar{q} \to$ hadrons (usually two jets)

For each event measure $\vec{x} = (x_1, \ldots, x_n)$.
According to Neyman–Pearson, to select WWs we should cut on

$$t(\vec{x}) = \frac{f(\vec{x}|H_0)}{f(\vec{x}|H_1)},$$

but we need to know $f(\vec{x}|H_0)$ and $f(\vec{x}|H_1)$.
In practice, get these from Monte Carlo event generator:

Generate events, for each, obtain $\vec{x}$ and enter into n-dimensional histogram. If e.g. M bins per component, total number of cells in $\vec{x}$-space $= M^n$

Approximate $f(\vec{x}|H)$ by probability to be in corresponding cell, i.e. determine M^n parameters. But n is potentially large!

⇒ prohibitively large number of cells to populate with MC data.

Compromise solution:

Make Ansatz for form of $t(\vec{x})$ with fewer parameters; determine the parameters (e.g. using MC) to give best discrimination between H_0 and H_1.

Linear test statistic

Ansatz: $t(\vec{x}) = \sum_{i=1}^{n} a_i x_i = \vec{a}^T \vec{x}$

A choice of $\vec{a}$ gives certain pdfs $g(t|H_0)$, $g(t|H_1)$.

Choose the a_i to maximize 'separation' between $g(t|H_0)$, $g(t|$

→ Must define 'separation'.

We have the expectation values and covariances,

$$(\mu_k)_i = \int x_i f(\vec{x}|H_k)\, d\vec{x},$$

$$(V_k)_{ij} = \int (x - \mu_k)_i \, (x - \mu_k)_j \, f(\vec{x}|H_k)\, d\vec{x},$$

$k = 0, 1$ (hypothesis),

$i, j = 1, \ldots, n$ (component of $\vec{x}$).

Similarly for mean and variance of $t(\vec{x})$,

$$\tau_k = \int t(\vec{x}) f(\vec{x}|H_k)\, d\vec{x} = \vec{a}^T \vec{\mu}_k,$$

$$\Sigma_k^2 = \int (t(\vec{x}) - \tau_k)^2 \, f(\vec{x}|H_k)\, d\vec{x} = \vec{a}^T \, V_k \, \vec{a}.$$

We should require:

large $|\tau_0 - \tau_1|$,

small Σ_0^2, Σ_1^2 (pdfs tightly concentrated about their means

Linear test statistic (continued)

Fisher defines as a measure of separation

$$J(\vec{a}) = \frac{(\tau_0 - \tau_1)^2}{\Sigma_0^2 + \Sigma_1^2}.$$

The numerator of $J(\vec{a})$ is

$$(\tau_0 - \tau_1)^2 = \sum_{i,j=1}^{n} a_i a_j (\mu_0 - \mu_1)_i (\mu_0 - \mu_1)_j$$

$$= \sum_{i,j=1}^{n} a_i a_j B_{ij} = \vec{a}^T \, B \, \vec{a} \, .$$

The denominator is

$$\Sigma_0^2 + \Sigma_1^2 = \sum_{i,j=1}^{n} a_i a_j (V_0 + V_1)_{ij} = \vec{a}^T \, W \, \vec{a} \, .$$

This gives $J(\vec{a}) = \dfrac{\vec{a}^T \, B \, \vec{a}}{\vec{a}^T \, W \, \vec{a}} = \dfrac{\text{separation between classes}}{\text{separation within classes}}$

Set $\dfrac{\partial J}{\partial a_i} = 0 \quad \Rightarrow \quad \vec{a} \propto W^{-1}(\vec{\mu}_0 - \vec{\mu}_1)$

This defines Fisher's linear discriminant function, determined up to a scale factor for $\vec{a}$.

R.A. Fisher, *Ann. Eugen.* 7 (1936) 179.

Neural networks (1)

Used in neurobiology, pattern recognition, financial forecasting . .

here, neural nets are just a type of test statistic.

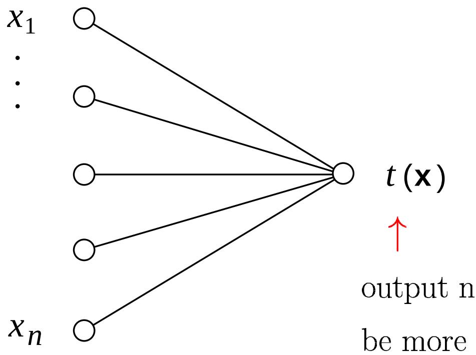
Suppose we take $t(\vec{x})$ to have the form

$$t(\vec{x}) = s\left(a_0 + \sum_{i=1}^{n} a_i x_i\right)$$

where $s(u) = (1 + e^{-u})^{-1}$ (the 'activation function')

This is the single-layer perceptron.

$s(\cdot)$ is monotic $\Rightarrow$ equivalent to linear $t(\vec{x})$.

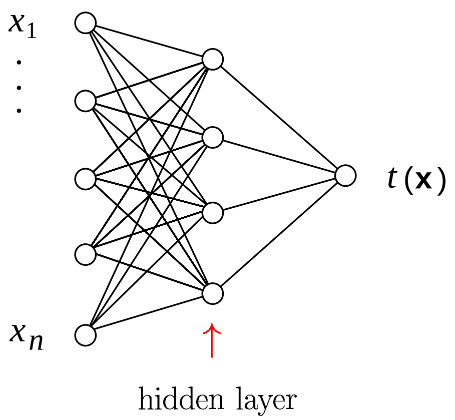


↑ output node (could be more than one)

↑ input layer

Neural networks (2)

Generalize this to the multilayer perceptron:



The output is defined by $t(\vec{x}) = s\left(a_0 + \sum_{i=1}^{m} a_i h_i(\vec{x})\right)$,

where the h_i are functions of the nodes in the previous layer,

$$h_i(\vec{x}) = s\left(w_{i0} + \sum_{j=1}^{n} w_{ij} x_j\right) .$$

$a_i,\ w_{ij}\ =$ weights (connection strengths)

Easy to generalize to arbitrary number of layers.
Feed-forward net: values of a node depend only on earlier layers, usually only on previous layer → 'network architecture'

More nodes → neural net gets closer to optimal $t(\vec{x})$, but more parameters need to be determined.

Neural networks (3)

Parameters usually determined by minimizing an error function,

$$\mathcal{E} = E_0[(t - t^{(0)})^2] \ + \ E_1[(t - t^{(1)})^2] \, ,$$

where $t^{(0)}$, $t^{(1)}$ are target values, e.g. 0 and 1 for logistic sigmoi cf. least squares principle with Fisher discriminant.

In practice, replace expectation values by averages of training dat from Monte Carlo. (Adjusting parameters = network 'learning'.)

In general this can be tricky; fortunately, programs like `JETNET` do it for you, e.g. with 'error back-propogation'.

For more information see

L. Lönnblad et al., *Comput. Phys. Commun.* 70 (1992) 167;
C. Peterson, et al., *Comput. Phys. Commun.* **81** (1994) 185;
C.M. Bishop, *Neural Networks for Pattern Recognition*,
  Clarendon Press, Oxford (1995);
John Hertz, et al., *Introduction to the Theory of Neural*
  Computation, Addison-Wesley, New York (1991);
B. Müller et al., *Neural Networks: an Introduction*, 2nd editi
  Springer, Berlin (1995).

Neural networks (4)

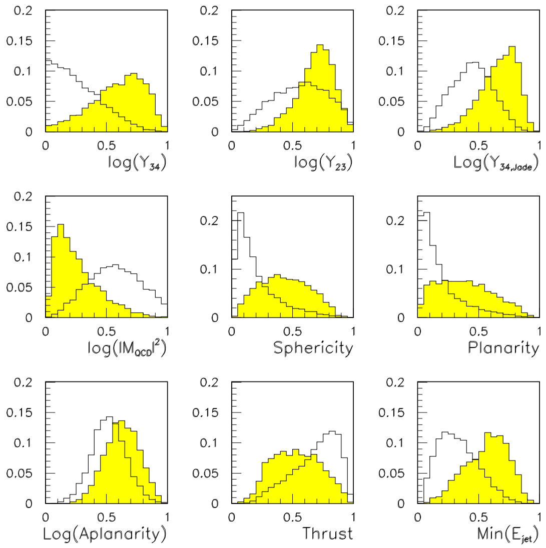
An example with WW event selection

(Garrido, Juste and Martinez, ALEPH 96-144)

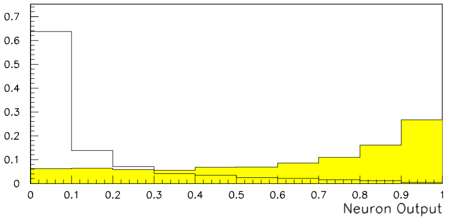
The input variables:

Shaded histograms: WW (signal)

Open histograms: $q\bar{q}$ (background)



The neural network output:



Choosing the input variables

Why not use all of the available input variables?

Fewer inputs → fewer parameters to be adjusted,

→ parameters better determined for finite training data.

Some inputs may be highly correlated → drop all but one.

Some inputs may contain little or no discriminating power between the hypotheses → drop them.

NN exploits higher moments of joint pdf $f(\vec{x}|H)$, but these may not be well modeled in training data.

→ better to have simpler $t(\vec{x})$ where you can 'understand what it's doing'.

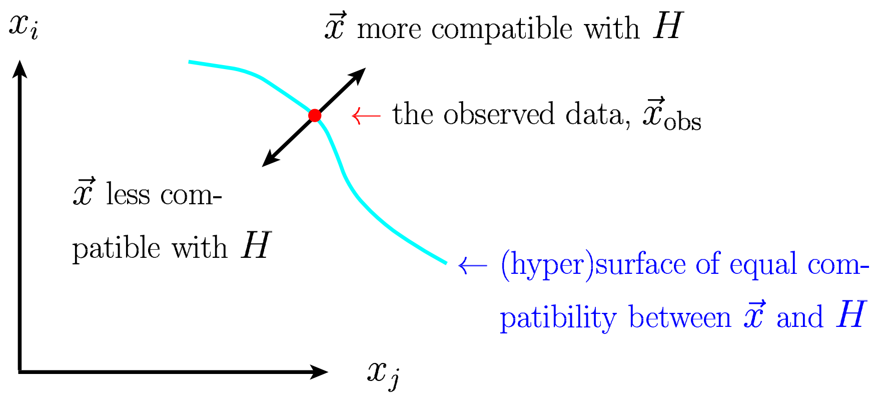
Recall that the purpose of the statistical test is usually to select objects for further study; e.g. select WW events, then measure their properties (e.g. particle multiplicity).

⇒ avoid input variables that are correlated with the properties of the selected objects which you want to study. (Not always easy; correlations may not be well known.)

Testing goodness-of-fit

Suppose hypothesis H predicts $f(\vec{x}|H)$ for some vector of data $\vec{x} = (x_1, \ldots, x_n)$.
We observe a single point in $\vec{x}$-space: $\vec{x}_{\mathrm{obs}}$.
What can we say about the validity of H in light of the data?

→ Decide what part of $\vec{x}$-space represents less compatibility with H than does the observed point $\vec{x}_{\mathrm{obs}}$. (Not unique!)



x_i

$\vec{x}$ more compatible with H

← the observed data, $\vec{x}_{\mathrm{obs}}$

$\vec{x}$ less compatible with H

← (hyper)surface of equal compatibility between $\vec{x}$ and H

x_j

Usually construct test statistic $t(\vec{x})$ whose value reflects level compatibility between $\vec{x}$ and H, e.g.

low t → data more compatible with H;
high t → data less compatible with H.

Since pdf $f(\vec{x}|H)$ known, the pdf $g(t|H)$ can be determined.

P-values

Express 'goodness-of-fit' by giving the P-value (also called observed significance level or confidence level):

P = probability to observe data $\vec{x}$ (or $t(\vec{x})$) having equal or lesser compatibility with H as $\vec{x}_{\mathrm{obs}}$ (or $t(\vec{x}_{\mathrm{obs}})$)

This is not the 'probability' that H is true!

In classical statistics we never talk about $P(H)$.
In Bayesian statistics, treat H as a random variable; use Bayes' theorem (here symbolically) to obtain

$$P(H|t) = \frac{P(t|H)\pi(H)}{\int P(t|H)\,\pi(H)\,dH}$$

where $\pi(H)$ is the prior probability for H; normalize by integrating (or summing) over all possible hypotheses.
For now stick with classical approach, i.e. our final answer is the P-value.

N.B. No alternative hypotheses mentioned.

N.B. P-value is a random variable. Previously considered significance level was a constant, specified before the test.

If H true, then (for continuous $\vec{x}$) P is uniform in $[0, 1]$.
If H not true, then pdf of P is (usually) peaked closer to 0.

An example of a goodness-of-fit test

Probability to observe n_{h} heads in N coin tosses is:

$$f(n_{\mathrm{h}}; p_{\mathrm{h}}, N) = \frac{N!}{n_{\mathrm{h}}!(N-n_{\mathrm{h}})!} p_{\mathrm{h}}^{n_{\mathrm{h}}} (1-p_{\mathrm{h}})^{N-n_{\mathrm{h}}}$$

Hypothesis H: the coin is fair ($p_{\mathrm{h}} = p_{\mathrm{t}} = 0.5$)

Take as goodness-of-fit statistic $t = |n_{\mathrm{h}} - \frac{N}{2}|$.

We toss the coin $N = 20$ times and get 17 heads, i.e. $t_{\mathrm{obs}} = 7$.

Region of t-space with equal or lesser compatibility:

$$t \geq 7$$

$$P\text{-value} = P(n_{\mathrm{h}} = 0, 1, 2, 3, 17, 18, 19 \text{ or } 20) = 0.0026$$

So does this mean H is false? P-value does not answer this question; it only gives the probability of obtaining such a level of discrepancy (or higher) with H as that observed.

P-value = probability of obtaining such a bizarre result 'by chance'.

A philosophical objection (but not a real problem):

Could have defined experiment to end after at least 3 heads and tails; in ours this happened to occur after 20 tosses. In such an experiment, the P-value is 0.00072!

Pragmatist's solution: 'repetition of experiment' taken to mean repetition with same number of trials per experiment.

The significance of an observed signal

Suppose we observe n events; these can consist of:

n_{b} events from known processes (background)
n_{s} events from new processes (signal)

If $n_{\mathrm{b}}, n_{\mathrm{s}}$ are Poisson r.v.s with means $\nu_{\mathrm{b}}, \nu_{\mathrm{s}}$, $\Rightarrow$ $n = n_{\mathrm{s}} + n_{\mathrm{b}}$ is also Poisson, mean $\nu = \nu_{\mathrm{s}} + \nu_{\mathrm{b}}$ (cf. SDA Chapter 10):

$$P(n; \nu_{\mathrm{s}}, \nu_{\mathrm{b}}) = \frac{(\nu_{\mathrm{s}} + \nu_{\mathrm{b}})^n}{n!} e^{-(\nu_{\mathrm{s}} + \nu_{\mathrm{b}})}$$

Suppose $\nu_{\mathrm{b}} = 0.5$ and we observe $n_{\mathrm{obs}} = 5$.

Should we claim evidence for a new discovery?

Hypothesis H: $\nu_{\mathrm{s}} = 0$, i.e. only background present.

$$P\text{-value} = P(n \geq n_{\mathrm{obs}})$$

$$= \sum_{n=n_{\mathrm{obs}}}^{\infty} P(n; \nu_{\mathrm{s}} = 0, \nu_{\mathrm{b}})$$

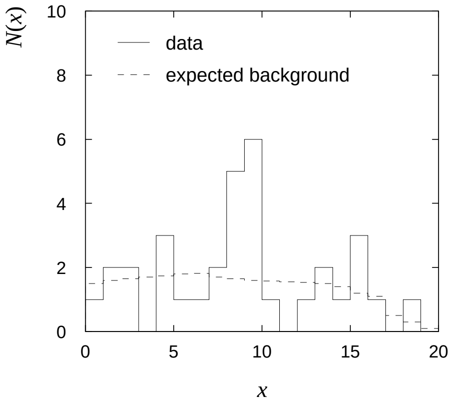
$$= 1 - \sum_{n=0}^{n_{\mathrm{obs}}-1} \frac{\nu_{\mathrm{b}}^n}{n!} e^{-\nu_{\mathrm{b}}}$$

$$= 1.7 \times 10^{-4}$$

$$(\neq P(\nu_{\mathrm{s}} = 0)!)$$

The significance of a peak

Suppose in addition to counting events, we measure x for each.



← Histogram of observed and expected data. Each bin is a Poisson variable.

In the 2 bins with peak, 11 entries found, $\nu_{\rm b} = 3.2$,

$$P(n \geq 11; \nu_{\rm b} = 3.2; \nu_{\rm s} = 0) = 5.0 \times 10^{-4}$$

But…did we know where to look for the peak?

→ give $P(n \geq 11)$ in any 2 adjacent bins.

Is the observed width consistent with the expected x resolution?

→ take x window several times expected resolution

How many bins × distributions have we looked at?

→ look at a thousand of them, you'll find a 10^{-3} effect.

Did we adjust the cuts to 'enhance' the peak?

→ freeze cuts, repeat analysis with new data.

How about the bins to the sides of the peak … (too low!)

Should we publish???

Pearson's χ^2 test

Test statistic for comparing observed data $\vec{n} = (n_1, \ldots, n_N)$ to predicted expectation values $\vec{\nu} = (\nu_1, \ldots, \nu_N)$:

$$\chi^2 = \sum_{i=1}^{N} \frac{(n_i - \nu_i)^2}{\nu_i}$$

If n_i are independent Poisson r.v.s with means ν_i, and all ν_i not too small (rule of thumb: all $\nu_i \geq 5$), then χ^2 will follow the chi-square pdf for N dof. The observed χ^2 then gives a P-value:

$$P = \int_{\chi^2}^{\infty} f(z; N)\, dz$$

where $f(z; N)$ is the chi-square pdf for N degrees of freedom.

Recall for chi-square pdf, $E[z] = N$,

→ often give χ^2/N as measure of level of agreement

Better to give χ^2, N separately …

$\chi^2 = 15$, $N = 10$ → P-value $= 0.13$

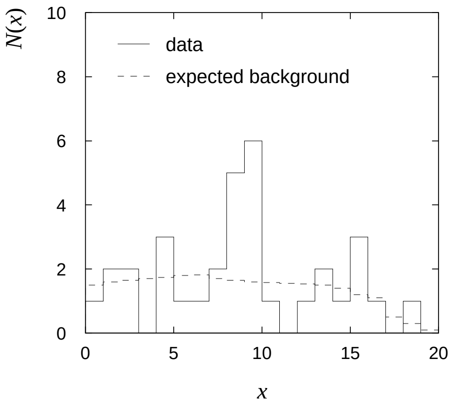
$\chi^2 = 150$, $N = 100$ → P-value $= 9.0 \times 10^{-4}$

If $n_{\rm tot} = \sum_{i=1}^{N} n_i$ is fixed, n_i are binomial, $p_i = \nu_i / n_{\rm tot}$,

$$\chi^2 = \sum_{i=1}^{N} \frac{(n_i - p_i n_{\rm tot})^2}{p_i n_{\rm tot}}$$

will follow chi-square for $N - 1$ dof (all $p_i n_{\rm tot} >> 1$).

Example of χ^2 test



$\leftarrow$ This gives

$$\chi^2 = \sum_{i=1}^{N} \frac{(n_i - \nu_i)^2}{\nu_i}$$

$$= 29.8 \text{ for } N = 20 \text{ dof.}$$

But… many bins have few (or no) entries,

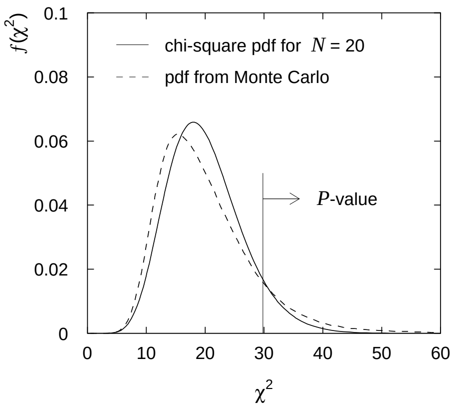
$\rightarrow$ here χ^2 will not follow chi-square pdf.

Pearson's χ^2 still usable as a test statistic, but to compute P-value first get $f(\chi^2)$ from Monte Carlo:

Generate n_i from Poisson, mean ν_i, $i = 1, \ldots, N$,

compute χ^2, record in histogram,

repeat experiment many times (here 10^6).



Using pdf from MC gives

$P = 0.11$

Chi-square pdf would give

$P = 0.073$

Parameter estimation: general concepts

Consider n independent observations of an r.v. x,

$\rightarrow$ sample of size n

Equivalently, single observation of an n-dimensional vector:

$$\vec{x} = (x_1, \ldots, x_n)$$

The x_i are independent $\Rightarrow$ joint pdf for the sample is

$$f_{\text{sample}}(\vec{x}) = f(x_1) f(x_2) \cdots f(x_n)$$

Task: given a data sample, infer properties of $f(x)$.

$\rightarrow$ construct functions of the data to estimate various properties of $f(x)$ (mean, variance, …)

Often, form of $f(x)$ hypothesized, value of parameter(s) unknow

$\rightarrow$ given form of $f(x;\theta)$ and data sample, estimate θ

Statistic = function of the data

Estimator = statistic used to estimate some property of a pdf

notation: estimator for θ is $\hat{\theta}$ (hat means estimator)

Estimate = an observed value of an estimator (often: $\hat{\theta}_{\text{obs}}$)

N.B. $\hat{\theta}(\vec{x})$ is a function of a (vector) random variable,

$\Rightarrow$ it is itself a random variable, characterized by a pdf $g(\hat{\theta})$

with an expectation value (mean), variance, etc.

Estimators

How do we construct an estimator $\hat{\theta}(\vec{x})$?

There is no golden rule on how to construct an estimator.

Construct estimators to statisfy (in general conflicting) criteria.

As a start, require consistency: $\lim_{n \to \infty} \hat{\theta} \; = \; \theta$

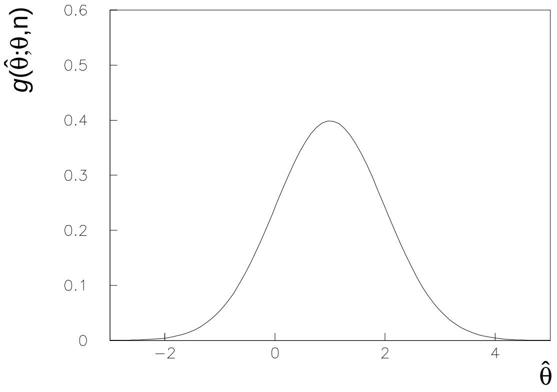
i.e. as size of sample increases, estimate converges to true value:

for any $\epsilon > 0, \; \lim_{n \to \infty} P(|\hat{\theta} - \theta| > \epsilon) = 0.$

N.B. convergence in the sense of probability, i.e. no guaranty that any particular $\hat{\theta}_{\text{obs}}$ will be within any given distance of θ.

Properties of estimators

Consider the pdf of $\hat{\theta}$ for a fixed sample size n:



N.B. $g(\hat{\theta};\theta,n)$ depends on true (unknown!) parameter θ.

We don't know θ, just a single value $\hat{\theta}_{\text{obs}}$.

Properties of $g(\hat{\theta};\theta,n)$:

variance $V[\hat{\theta}] \; = \; \sigma^2_{\hat{\theta}}.$ $\quad$ ($\sigma_{\hat{\theta}}$ = 'statistical error')

bias $b \; = \; E[\hat{\theta}] \; - \; \theta$ $\quad$ ('systematic error', depends on n

For many estimators we will have $\sigma_{\hat{\theta}} \propto \frac{1}{\sqrt{n}}, \quad b \propto \frac{1}{n}.$

Sometimes consider mean squared error:

$$\text{MSE} = V[\hat{\theta}] \; + \; b^2$$

In general, there is a trade-off between bias and variance,

→ often require minimum variance among estimators with 0 bias

Estimator for the mean (expectation value)

Consider n measurements of r.v. x, $x_1, \dots, x_n$, we want an estimator for $\mu = E[x]$. Try arithmetic mean of the x_i:

$$\hat{\mu} = \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \text{(the sample mean)}$$

If $V[x]$ finite, $\overline{x}$ is a consistent estimator for μ, i.e.

$$\text{for any } \epsilon > 0, \; \lim_{n\to\infty} P\left(\left| \frac{1}{n}\sum_{i=1}^{n} x_i - \mu \right| \geq \epsilon \right) = 0 \, .$$

This is the Weak Law of Large Numbers. Compute expectation value:

$$E[\overline{x}] = E\left[\frac{1}{n}\sum_{i=1}^{n} x_i \right] = \frac{1}{n}\sum_{i=1}^{n} E[x_i] = \frac{1}{n}\sum_{i=1}^{n} \mu = \mu$$

→ $\overline{x}$ is an unbiased estimator for μ . Compute variance:

$$V[\overline{x}] = E[\overline{x}^2] - (E[\overline{x}])^2 = E\left[\left(\frac{1}{n}\sum_{i=1}^{n} x_i \right) \left(\frac{1}{n}\sum_{j=1}^{n} x_j \right) \right] - \mu^2$$

$$= \frac{1}{n^2}\sum_{i,j=1}^{n} E[x_i x_j] - \mu^2$$

$$= \frac{1}{n^2}\left[(n^2 - n)\mu^2 + n(\mu^2 + \sigma^2) \right] - \mu^2 = \frac{\sigma^2}{n}$$

where σ^2 is the variance of x, and we used

$$E[x_i x_j] = \mu^2 \text{ for } i \neq j \text{ and } E[x_i^2] = \mu^2 + \sigma^2 \, .$$

Estimator for the variance

Suppose mean μ and variance $V[x] = \sigma^2$ both unknown.

Estimate σ^2 with the sample variance:

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - \overline{x})^2 = \frac{n}{n-1}\left(\overline{x^2} - \overline{x}^2 \right)$$

Factor of $1/(n-1)$ included so that $E[s^2] = \sigma^2$ (i.e. no bias

If $\mu = E[x]$ is known a priori,

$$S^2 = \frac{1}{n}\sum_{i=1}^{n} (x_i - \mu)^2 = \overline{x^2} - \mu^2$$

is an unbiased estimator for σ^2.

Computing the variance of s^2 (long calculation!) gives

$$V[s^2] = \frac{1}{n}\left(\mu_4 - \frac{n-3}{n-1}\mu_2^2 \right)$$

where μ_k is kth central moment (e.g. $\mu_2 = \sigma^2$).

The μ_k can be estimated using

$$m_k = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - \overline{x})^k$$

Estimator for covariance and correlation coefficient

To estimate the covariance $V_{xy} = \mathrm{cov}[x, y]$, use

$$\widehat{V}_{xy} = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y}) = \frac{n}{n-1} (\overline{xy} - \overline{x}\,\overline{y})$$

which is unbiased.

For the correlation coefficient $\rho = \dfrac{V_{xy}}{\sigma_x \sigma_y}$, use

$$r = \frac{\widehat{V}_{xy}}{s_x s_y} = \frac{\Sigma_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\left(\Sigma_{j=1}^{n} (x_j - \overline{x})^2 \cdot \Sigma_{k=1}^{n} (y_k - \overline{y})^2 \right)^{1/2}}$$

$$= \frac{\overline{xy} - \overline{x}\,\overline{y}}{\sqrt{(\overline{x^2} - \overline{x}^2)\,(\overline{y^2} - \overline{y}^2)}} \, .$$

r has a bias which goes to zero as $n \to \infty$.

In general, pdf $g(r; \rho, n)$ is complicated; for Gaussian x, y,

$$E[r] = \rho - \frac{\rho(1 - \rho^2)}{2n} + O(n^{-2})$$

$$V[r] = \frac{1}{n} (1 - \rho^2)^2 + O(n^{-2})$$

(cf. R.J. Muirhead, *Aspects of Multivariate Statistical Theory*, Wiley, New York, 1982.)

Lecture 2 summary

- **Statistical tests:** test whether data stand in agreement with predicted probabilities, i.e., hypotheses. Critical region, significan level, power, (related to efficiency, purity).
- **Fisher discriminants, neural networks, etc.:** reduce data vector $\vec{x}$ to a single (or few) component function $t(\vec{x})$. Compact data while retaining ability to discriminate between hypotheses.
- **Goodness-of-fit tests:** quantify level of agreement between da and hypothesis with P-value.
- **The significance of a signal:** often give P-value of hypothes that only background present.
- **Introduction to parameter estimation:** try to minimize b variance. Simple estimators for mean, variance, covariance.