

# Statistical tools for nuclear experiments, 3

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# Hypothesis test

Examples:

- is the detected particle a pion or a kaon ?
- is my level scheme regular or chaotic ?
- does my data support model A or model B ?

**The dilemma:** *exclude correct results vs. include wrong ones*  
two types of error (probability  $\alpha$  and  $\beta$ ), need to optimize. . .

Significance level ( $\alpha$ ) = probability of excluding correct result

Power ( $1 - \beta$ ) = probability of excluding wrong result

Tests should be powerful, consistent (and without bias).

**B8.1, C4.1, J10, P36.2**

# Neyman-Pearson test

A test consists (for our purpose) of two things:

- an algorithm giving a number  $x$
- specification of which region of  $x$  is accepted, which rejected

Let our hypothesis give distribution  $P_H(x)$  and the alternative hypothesis  $P_A(x)$ .

The **Neyman-Pearson test** uses the likelihood ratio  $P_A(x)/P_H(x)$  to rank the  $x$ -regions; low values accepted, high ones rejected.

There is the “best test” for cases without fit parameters (“simple hypotheses”).

# Likelihood ratio test

If your hypothesis/model has parameters one may often rephrase into a **likelihood ratio test** using the standard likelihood  $L(x; a)$ . This is the case when you wish to test that the parameters  $a$  belong to a subset  $\Omega_0$  of the total parameter-space  $\Omega_{tot}$ .

The **maximum likelihood ratio** is:

$$\lambda = \max_{a \in \Omega_0} L(x; a) / \max_{a \in \Omega_{tot}} L(x; a), \quad 0 \leq \lambda \leq 1$$

Asymptotically  $-2 \ln \lambda$  has a  $\chi^2$ -distribution (number of dof = difference in number of parameters in  $\Omega_0$  and  $\Omega_{tot}$ ).

Example: Poisson likelihood  $\chi^2_{\lambda}$ ,  $n_i = y_i$  versus  $n_i$  free.

Dof =  $N$  – number of parameters in  $y$ .

## J10.5

# Goodness-of-fit

**Question:** does the model fit my data ?

— a subset of testing, but only one “hypothesis” specified.

Most often no unique best procedure !

Two things to consider:

- Do you really want the answer ??
- If yes, do you care sufficiently to go beyond  $\chi^2$  ?

Tests can be combined. . .

# The chi-square test

*All time favourite:* (Pearson's) chi-square test for histograms.

$$\chi^2 = \sum_{i=1}^M \frac{(n_i - Np_i)^2}{Np_i}, \quad p_i = \int_i y dx$$

Neyman modification:  $Np_i \rightarrow n_i$  in denominator.

Asymptotically a  $\chi^2$ -distribution, works better when bins are chosen so that  $p_i$  about equal.

“Too nice to be true”: # dof = # points – # parameters

Very general method — therefore often not powerful.

**B8.3.1, C7.5, J11.2**

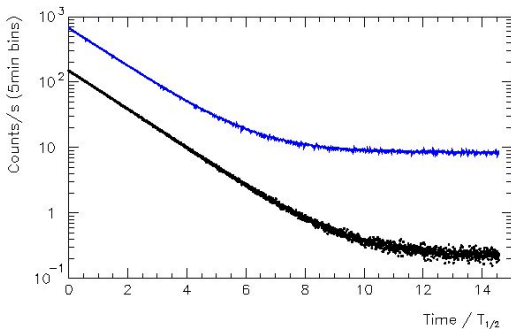
# Example: Halflife of $^{64}\text{Cu}$

Gate on  $\gamma$ ,  
correct for  
deadtime

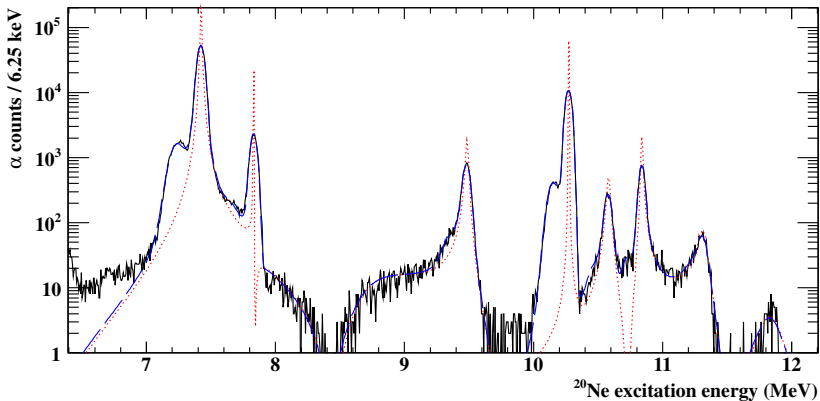
$$\chi^2 = 2222$$

$$\nu = 2228$$

Courtesy  
Hans Fynbo





Example:  $^{20}\text{Na}$   $\beta\alpha$  decay

$$\chi^2/\nu = 2.21, \nu = 800$$

# Problems with chi-square

A technical problem: is the  $\chi^2$  value acceptable ?

Can use that  $\sqrt{2\chi^2}$  is, for  $\nu > 30$ , Gaussian with mean  $\sqrt{2\nu - 1}$  and standard deviation 1.

I.e.  $\sqrt{2\chi^2} - \sqrt{2\nu - 1}$  gives the number of  $\sigma$ 's.

The deeper problems:

- Finite sample  $\rightarrow$  when does the asymptotic behaviour set in ?
- Throws away much information
  - insensitive to sign of deviation
  - cannot see systematic trends (correlated deviations)
- Sensitive to “outliers” (deviation squared !)

May combine with complimentary test, e.g. run test.

## EDF tests

Compare **Empirical Distribution Function** (EDF) with cumulative distribution.

$$\text{EDF}(x) = (\text{number of data points} \leq x) / N$$

Kolmogorov(-Smirnov), Cramér-von Mises, Anderson-Darling...

*Pros*

Easy to interpret for  
parameter-free distributions.  
Distribution-free.

*Cons*

Need Monte-Carlo when  
parameters are fitted.  
Mainly for 1-D data.

**B8.3.3, J11.4**

(Illustrated with figure 4 + table 1 from [H. Jeppesen et al., Nucl. Phys. A709 \(02\) 119](#))

# P-values etc

Prove a new effect *vs.* disprove “null hypothesis” ??

$P$ -value = probability of observed data (or more extreme departures) *if* the null hypothesis is true.

If  $P < \alpha$  (significance level), null hypothesis is rejected. Typically use  $\alpha = 0.05$ . **Particle physics want positive  $5\sigma$  signal.**

[Are most published research findings in medicin “false positives” ?  
J.P.A. Ioannidis, PLoS Medicine vol 2, issue 8 (2005) e124]

$P$  is *not* the probability of data arising by chance.

$P$  is *not* the probability of the null hypothesis, need Bayesian methods/decision theory to decide on models

# Example: $\chi^2$ per dof and P-values

As figure 36.2 in **P**, that gives “reduced”  $\chi^2$  with corresponding P-values, shows explicitly:

*Always quote  $\chi^2$  and  $n$ , never just  $\chi^2/n$  !*

or use the  $\sqrt{2\chi^2}$ -rule...

Illustrated with figure in W review, **P** p 470:

$\chi^2$  and dof for two sets of W boson mass measurements.

# What if $\chi^2$ is bad ?

*In principle:* reject model, incompatible with data !

*In practice:* find out where the large  $\chi^2$  comes from ([plot of residuals](#)).

If from a specific feature, it may not affect physics results (parameter errors etc).

If no obvious cause (and you insist in using the model):

enlarge error bars by  $\sqrt{\chi^2/\nu}$

a PDG recipe — always think before use. . .

# Other procedures

Monte Carlo simulations !

*Many* other tests available: Shapiro-Wilk test, run test, ranking tests . . .

Neural networks.

Bayesians employ “Bayes factor” for testing (ratio of posterior probability of two models — related to likelihood ratio).