

Introduction to statistics

Summer internship
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Disclaimer & Goal:

- 30 minutes: Way too short to give a course on statistics
 - Covering important notions only, without demonstration
- Goal: Cover basic concepts that you might come across during the internship
- Courses on statistics:
 - “Statistics for Nuclear and Particle Physicists” Pr. Louis Lyons

Outline:

- Experimental error
- Distribution & Probability / Sample of events
- Important distributions – Central Theorem
- Error propagation
- Hypothesis testing: The χ^2 example

Experimental error

Any experimentally measured quantity has an uncertainty

Reflecting the precision of the measure

Example:

The speed of light is $c = 2.99792458 \times 10^8 \text{ m/s}$

A new experiment gives $c = (2.9900 \pm \sigma) \times 10^8 \text{ m/s}$

- $\sigma = 0.01$: New result is consistent with previous result
- $\sigma = 0.001$: New result is inconsistent with previous result
 - Either: We have made a new discovery
 - Or: Either the new value or error is wrong
- $\sigma = 1.0$: The new result is irrelevant

Experimental error

2 types of experimental errors:

- **Random/Statistical:** Inability to measure w infinite accuracy
 - Opinion polls, counting radioactive decays
- **Systematic:** “In the nature of our measure”: Often points to mis-calibration of device, mis-calibration that we must measure & include in our final result
 - We know that 100 atoms of Cesium decayed. We measure only 98 decay products: Systematic uncertainty of 2% specific to measuring device

Distribution & Probability

Distribution n(x): Describes how often a value of the variable x occurs in a definite sample of Data

<u>Range</u>	<u>x variable</u>	<u>n(x)</u>
[0,7]	Number of days in 1 week	N(Sunny days)
[-13.6,0] eV	Energy states of H atom	N(Atoms w electrons w E=x @ 10K)
[0,∞[Hours to understand stats	N(Person having understood after x hours)

Probability p(x): That with sample of N measurements, the value x is obtained n_x times

$$p(x) = \lim_{N \rightarrow \infty} (n_x / N) \quad p(x) \in [0,1]$$

Distributions/Probabilities are characterized mainly by 2 quantities:

Mean/Expectation value: $E(x) = \int x p(x) dx$

Variance: $\sigma^2(x) = \int (x - E(x))^2 p(x) dx$

During estagio:

- Most of the time
 - $p_T, E, (r, \phi, \eta)$ of a reconstructed particle
- If you use root: "E(x)" & σ will be given to you
 - But now you know what they correspond too :-)

Sample of events

For a set of N separate measurements of $x = \{x_1, \dots, x_n\}$, how can we estimate the expectation value & variance ?

$\bar{x} = (1/N) \sum_i x(i)$: Nothing else than $E(x) = \int x p(x) dx$ for a discrete case
where: $p(x) = p = 1/N$

$$\sigma^2(\bar{x}) = \sigma^2(x) / N:$$

Each of the measurements x has an uncertainty, but...

The more measurement we will have, the preciser the mean of all measurements will be

During estagio:

- The more your sample has events, the preciser your relative precision will be
- Relative uncertainty: $r = \sigma(\bar{x}) / \bar{x}$
 - Let's assume that: $\sigma(\bar{x}) = \sqrt{N}$ (Poisson, see next slides)
Then: $r = 1/\sqrt{N}$

Important distributions

Binomial:

When we have 2 possible outcomes of the experience

Probability: of having

m success

out of n trials

with p : Probability of success

q : Probability of failure $p+q=1$

$$p_n(m) = C_n^m p^m q^{n-m}$$

$$C_n^m = n!/m!(n-m)!$$

Expectation value:

$$E(m) = n p$$

Variance:

$$\sigma^2 = n p q$$

Examples: Tossing a coin & looking for e.g. heads

Detecting a produced particle or not: Can be used for calculating efficiency & its uncertainty

Important distributions

Poisson: When the probability of observing an event is small

Probability: $\lim_{N \rightarrow \infty} P_n(m) = \mu^m/m!$

$\mu =$ Mean counted events

Expectation value:

$$E(m) = \mu$$

Variance:

$$\sigma^2 = \mu$$

Example: Consider the very large number of radioactive nuclei. The probability that one of the nuclei decays within time interval Δt follows the Poisson distribution

**During
estagio:**

➤ When you count N events in a sample: The uncertainty on this number is \sqrt{N}

Important distributions

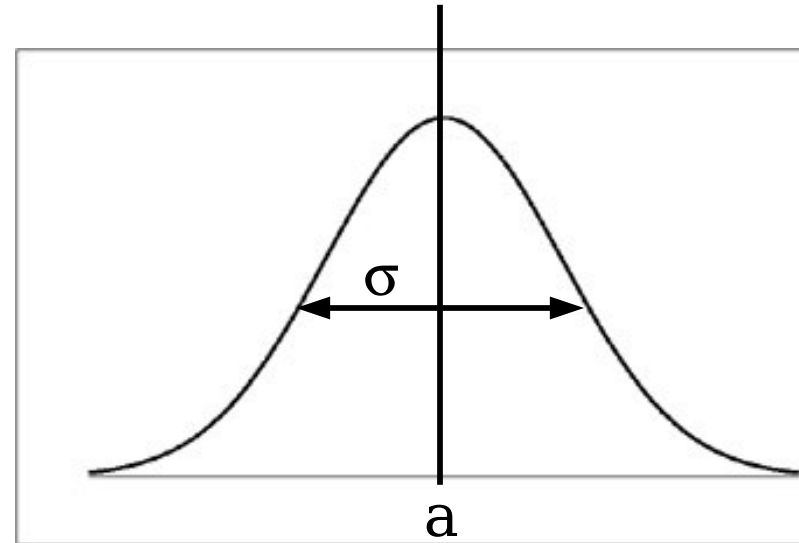
Gaussian:

Distribution:

$$G(x) = [1 / \sqrt{2\pi} \sigma] \exp[- (x-a)^2 / 2\sigma^2]$$

Expectation value: By definition: a

Variance: By definition: σ^2



Example: If the measure of a variable x (mean & variance) is well done, then the pull = $[x(\text{measured}) - x(\text{true}) / \sigma]$ follows a gaussian of $a=0$ & $\sigma=1$

During estagio:

- You might come across this distribution/probability when, i.e. fitting the resolution of a detector
- See next slide ;-)

Central limit theorem

If $x = \{x_1, \dots, x_n\}$ are a set of n independent variables all following an arbitrary distribution with mean a and variance σ^2 , then in the limit $n \rightarrow \infty$, their arithmetic mean $\bar{x} = (1/n) \sum_i x(i)$ follows a Gaussian distribution with mean a and variance σ^2/n

Error propagation

Imagine you are calculating an experimental quantity f which is a function of 2 numbers l & j

l : Counted number of reconstructed leptons

j : Counted number of reconstructed jets

What is the uncertainty on f ?

$$\sigma^2(\mathbf{f}) = (\delta l / \delta f)^2 \sigma^2(\mathbf{l}) + (\delta j / \delta f)^2 \sigma^2(\mathbf{j}) + 2(\delta l / \delta f)(\delta j / \delta f) \text{cov}(\mathbf{l}, \mathbf{j})$$

We are counting: Poisson is the uncertainty to take into account:
 $\sigma^2(\mathbf{l}) = l$; $\sigma^2(\mathbf{j}) = j$

$\text{cov}(\mathbf{l}, \mathbf{j})$: Covariance between l & j :

Measure of “how much l/j moves when j/l moves”

$$\text{cov}(\mathbf{l}, \mathbf{j}) = \rho(\mathbf{l}, \mathbf{j}) \cdot \sigma(\mathbf{l}) \cdot \sigma(\mathbf{j}) \quad \text{with } \rho(\mathbf{l}, \mathbf{j}) \in [0, 100]\%$$

Hypothesis testing: The χ^2 example

Imagine that we have $i \in [1, N]$ measurements $(O(i), \sigma(i))$ as a function of a variable x

We want to know the best hypothesis representing these observations, i.e. the function best fitting N observed Data

Finding a function f to test isn't a problem. The real question:
How can-I quantitatively test the goodness of my hypothesis ?

$$\chi^2 = \sum_i [(f(i) - O(i))^2 / \sigma(i)^2]$$

Accounts for: Each & full observation point $(O(i), \sigma(i))$
The tested hypothesis f

If the hypothesis is reasonably good:

$$\forall i \quad f(i) - O(i) \sim 1 \sigma(i) \rightarrow \chi^2/N(\text{Degrees freedom}) \sim 1$$

During estagio:

- root does this for you but now you know what does it correspond to :-)

Closing words

Always keep in mind that any quantity you measure, whatever the method of the measure, has an uncertainty

If you have stat problems and/or there are related points you would like to discuss: Let's discuss together, with your supervisor(s) bargassa@cern.ch

Wish you an interesting internship !