

Introduction to data analysis

DESY summer school 2023~~3~~4

Orel Gueta → Dan Parsons

DESY

~~August 3 & 4, 2023~~

July 25 + 26 2024

Acknowledgements and further reading

A lot of inspiration taken from the following lectures:

- > Louis Lyons - [Practical Statistics for Physicists](#).
- > Stephanie Hansmann-Menzemer - [Modern Methods of Data Analysis](#).
- > Andreas Hoecker - [Foundations of statistics](#).
- > Tommaso Dorigo - [Statistics Topics for Data Analysis in Particle Physics: an Introduction](#).
- > Kyle Cranmer - [Practical Statistics for Particle Physics](#).
- > Thomas Junk - [Data Analysis and Statistical Methods in Experimental Particle Physics](#).

Books:

- > [Particle data group statistics review](#) - concise, contains almost everything.
- > Glen Cowan - [Statistical data analysis](#).
- > Trevor Hastie et al. - [The Elements of Statistical Learning](#).
- > Olaf Behnke et al. - [Data Analysis in High Energy Physics: A Practical Guide to Statistical Methods](#).
- > J. VanderPlas et al. - [Introduction to astroML: Machine learning for astrophysics](#)



Alternative title could be

“Practical statistics for physicists”

Four lectures

- > Lectures 1 & 2 - Introduction to data analysis (~~orel.gueta~~^{daniel.parsons}@desy.de).
- > Lecture 3 & 4 - ~~Dan Parsons~~ - Machine Learning Techniques.

Outline

Iftach

- > Introduction
- > Probability and statistical distributions
- > Parameter and uncertainty estimation
- > Bayesian vs Frequentist
- > Hypothesis testing
- > Monte Carlo methods
- * Slightly biased towards particle physics

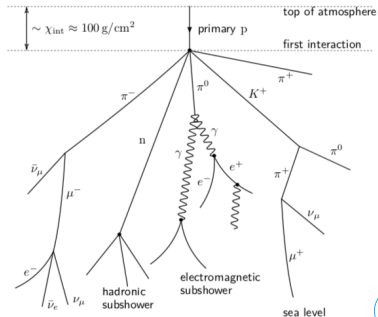
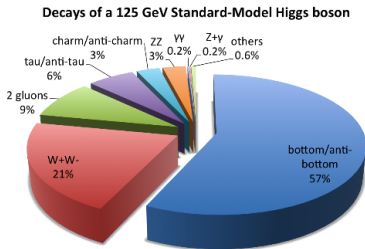
Please feel free to stop me and ask questions!



Introduction

Data analysis in physics involves a lot of probability and statistics.

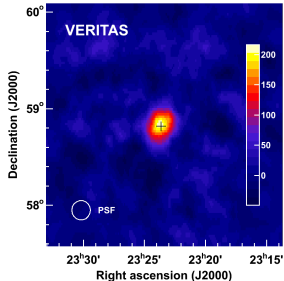
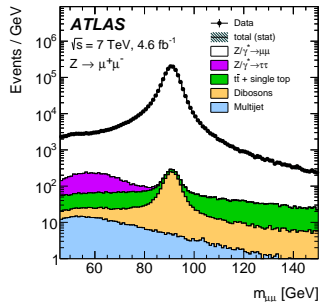
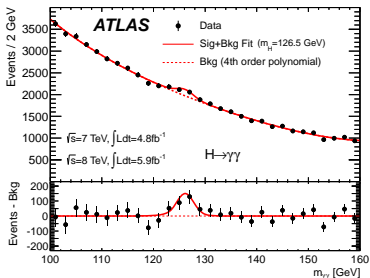
- Quantum phenomena is probabilistic in nature.
- So is the particle interaction with the detector (e.g., air shower fluctuations).
- Theory only provides probabilities (e.g., Higgs decay channels).
- Analyze large amounts of data and compare to probabilities.
- Utilize Monte Carlo methods to simulate probabilistic phenomena.



Introduction

Where is data analysis used?

- Measure a known parameter and its uncertainty (mass of the Z boson).
- Discover new phenomena (Higgs, γ -ray/neutrino source).
- Test your theory against the data (hypothesis testing).
- ➔ Extract as much as possible from data (experiments are expensive!)



Silly example

Introduction - cheating baker

Simple example of data visualization.

- > A restaurant owner orders 30 rolls every day.
- > The law in the country states that rolls must weigh ~ 75 grams;
- > After changing suppliers, the owner suspects that the new baker sells underweight rolls
- ⇒ Investigate! Weigh the rolls (1 gram resolution).

```
78, 66, 67, 64, 74, 58, 78, 66, 71, 68, 77, 59, 68, 68, 75, 64, 69, 65, 70, 72
64, 75, 74, 72, 74, 66, 69, 65, 68, 72, 66, 68, 66, 65, 66, 69, 64, 71, 78, 73
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66, 67, 70, 74, 70, 71, 70, 70, 64, 70, 69, 69, 72, 66, 69, 68, 72, 73, 65, 72
```

- > Raw list of weights is not very useful.



Introduction - cheating baker

A friend suggests to reduce the data,

- > combine the measurements, taking into account resolution;
- > assume the rolls are produced independently, e.g., neglect changes from week to week.

```
Weight[50] = 0 Weight[51] = 0 Weight[52] = 0 Weight[53] = 0 Weight[54] = 1
Weight[55] = 0 Weight[56] = 4 Weight[57] = 4 Weight[58] = 4 Weight[59] = 9
Weight[60] = 13 Weight[61] = 13 Weight[62] = 20 Weight[63] = 22 Weight[64] = 38
Weight[65] = 42 Weight[66] = 61 Weight[67] = 58 Weight[68] = 67 Weight[69] = 80
Weight[70] = 75 Weight[71] = 60 Weight[72] = 68 Weight[73] = 62 Weight[74] = 49
Weight[75] = 49 Weight[76] = 27 Weight[77] = 22 Weight[78] = 22 Weight[79] = 11
Weight[80] = 10 Weight[81] = 2 Weight[82] = 4 Weight[83] = 0 Weight[84] = 0
Weight[85] = 1 Weight[86] = 1 Weight[87] = 0 Weight[88] = 0 Weight[89] = 1
```

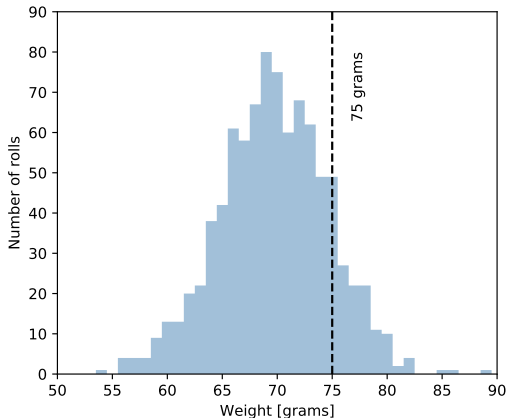
- > Can see that the majority of rolls weigh less than 75 grams.
- > Easier to understand the data this way, but still far from perfect.
- > Better idea to visualize the data?



Introduction - cheating baker

Visualize the data with a histogram,

- > immediately grasp the distribution of weights;
- > mean and standard deviation clearly visible.



- > New baker definitely cheating, rolls are about 5 grams too light.



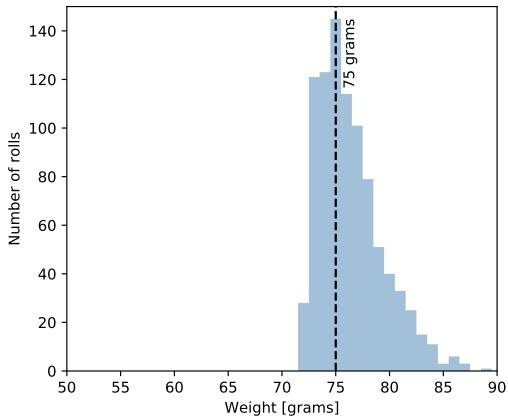
Introduction - cheating baker

- > The owner complains to the baker.
- > The baker promises to correct their ways → The restaurant owner keeps monitoring.



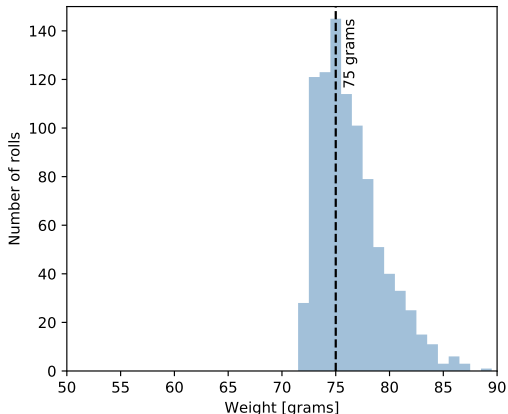
Introduction - cheating baker

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Introduction - cheating baker

- > The owner complains to the baker.
- > The baker promises to correct their ways → The restaurant owner keeps monitoring



- > A month later the owner sees the baker is still cheating, sending the restaurant the heaviest rolls and selling the light ones to others.

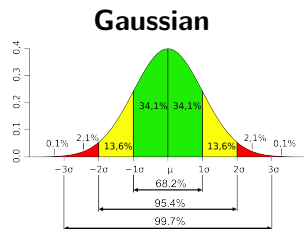


Statistical distributions

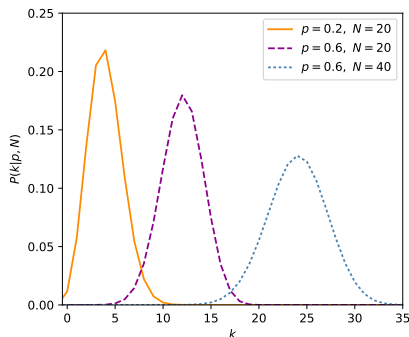
Statistical distributions

Measurements typically follow a distribution, identifying it could be important

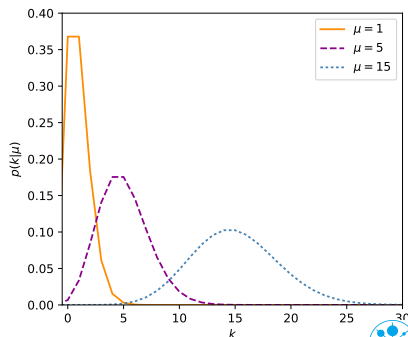
- correct determination of parameters;
- uncertainties estimation;
- for results interpretation (see example later).



Binomial

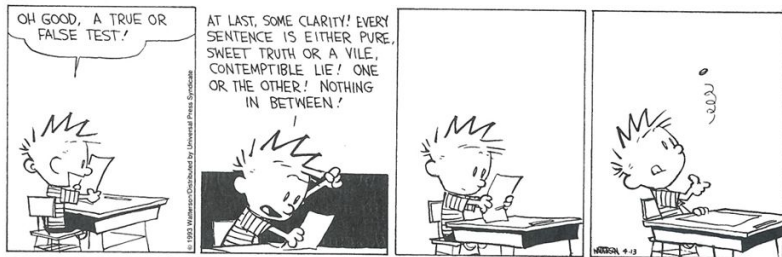


Poisson



Binomial distribution


Experiment has two outcomes,



For N “coins”, each with prob. of “success” p ,

$$P(k; p, N) = \frac{N!}{k!(N-k)!} p^k (1-p)^{N-k}$$

is the prob. of k successes.

- > What is the prob. to roll  34 times out of 100 throws?
- > Selection or reconstruction efficiency (prob. to reconstruct 560 γ 's with $p = 0.63$ and $N = 10^3$).



Binomial distribution

Characteristics,

- > Expectation value (mean, μ), $E[k] = \sum_k kP(k) = Np$.
- > Variance (σ^2), $E[(k - \langle k \rangle)^2] = E[k^2] - (E[k])^2 = Np(1 - p)$.

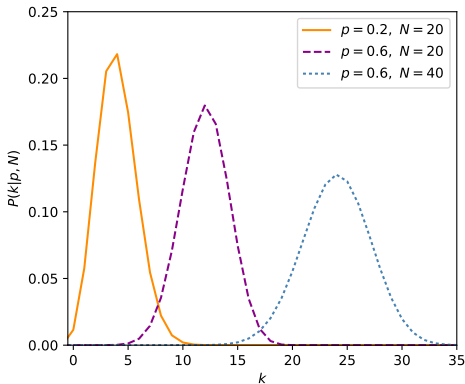
Intuitive, e.g., calculate for 8 coin flips.

Take into account when dealing with efficiencies

- > ROOT includes various options to use binomial errors for efficiency (e.g., TEfficiency). Similar tools exist for R and Python.

Limiting cases,

- > For $N \rightarrow \infty$, $p \rightarrow 0$
 $Np = \text{const.}$,
Binomial \rightarrow Poisson.
- > For $N \rightarrow \infty$, $p = \text{const.}$,
Binomial \rightarrow Gaussian.



Poisson distribution

Prob. of N independent events occurring in time interval Δt with constant rate μ ,

$$P(N; \mu) = \frac{\mu^N}{N!} e^{-\mu}$$

> Expectation value, $E[N] = \sum_N NP(N) = \mu$. Variance, $\sigma^2 = \mu$.

Where do we run into this dist.?



Poisson distribution

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Where do we run into this dist.?

> Number of decay events per second from a radioactive source;



Poisson distribution

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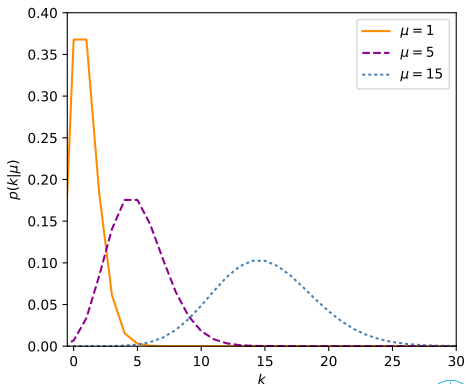
$$P(N; \mu) = \frac{\mu^N}{N!} e^{-\mu}$$

> Expectation value, $E[N] = \sum_N NP(N) = \mu$. Variance, $\sigma^2 = \mu$.

Where do we run into this dist.?

- > Number of decay events per second from a radioactive source;
- > Number of “rare” interactions occurring per bunch crossing at LHC;
- > Number events in a histogram bin.
- typical, $N \pm \sqrt{N}$ (what about 0 ± 0 ?).

When $\mu \rightarrow \infty$, Poisson \rightarrow Gaussian.



Importance of distribution identification

Example - evidence of quarks in air showers.

- > Researchers observed a track with 110 bubbles (average expected is 229, 55,000 tracks in total).
- > They assumed (correctly) bubble formation is a Poisson-distributed quantity.
- ⇒ Probability of observation $P \sim 10^{-13}$.
- ⇒ Particles with fractional charge!

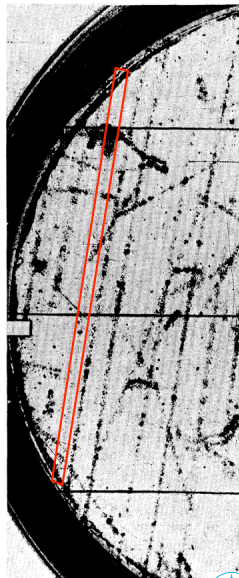
In fact,

- > each scatter of a charged particle off a nucleus produces ~ 4 droplets.
- ⇒ Both particle scattering and bubble formation are Poisson processes.
- ⇒ Need to use a compound Poisson distribution.
- > P to observe one 110 bubble track, $P \approx 5 \cdot 10^{-5}$;
- > Observing one such track out of 55,000, $P \sim 92\%$.

EVIDENCE OF QUARKS IN AIR-SHOWER CORES*

C. B. A. McCusker and I. Cairns

Cornell-Sydney University Astronomy Center, Physics Department, The University of Sydney, Sydney, Australia
(Received 3 September 1969)



Gaussian distribution

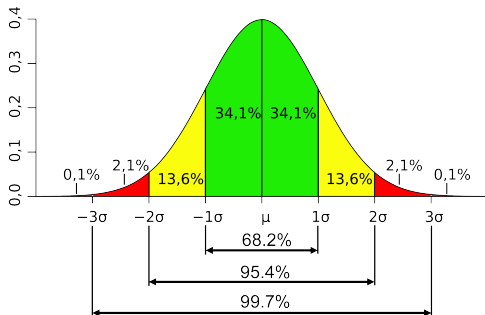
Probably the most common distribution (thanks to Central Limit Theorem),

$$P(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- > Expectation value, $E[x] = \mu$.
- > Variance, $\sigma^2 = \sigma^2$.
- > At $x = \mu \pm \sigma$, $y = y_{\max}/\sqrt{e} \sim 0.606 \times y_{\max}$.

Probability content often used

- > $\int_{-\sigma}^{+\sigma} P(x; \mu, \sigma) dx = 68.2\%$;
- > $\int_{-2\sigma}^{+2\sigma} P(x; \mu, \sigma) dx = 95.4\%$
- > etc.



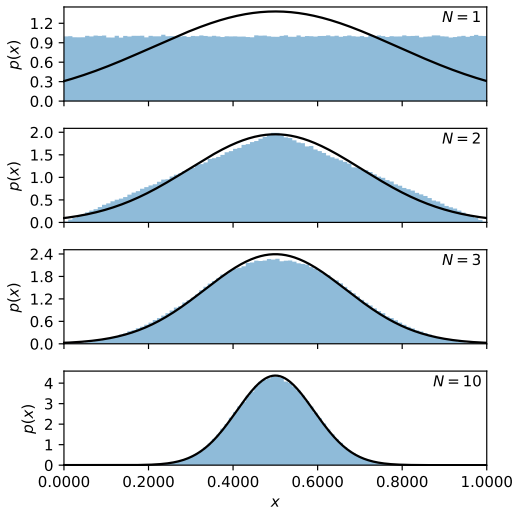
Central Limit Theorem

Idea:

- > pick k random variables from **any** distribution $Q(x)$;
- > repeat N times and calculate mean (or sum) between the variables;
- ⇒ the distribution of the mean values will be Gaussian.
- * $Q(x)$ should be well defined.

Illustration:

- > Uniform $Q(x)$;
- > Gaussian is shown for $\mu = 0.5$ and $\sigma = 1/\sqrt{12N}$;
- > Already for $N = 10$, Gaussian distribution observed.
- > Larger N for non-uniform $Q(x)$.



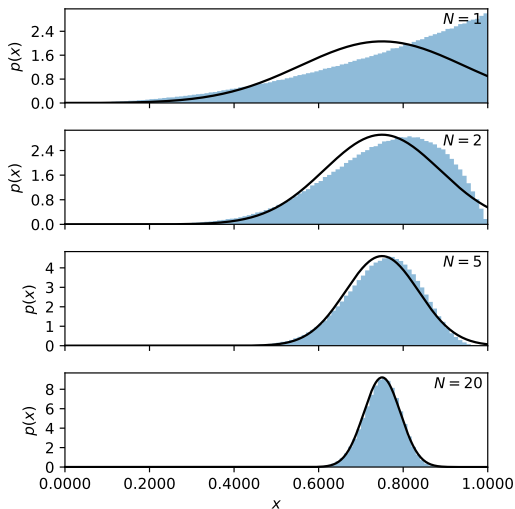
Central Limit Theorem

Idea:

- > pick k random variables from **any** distribution $Q(x)$;
- > repeat N times and calculate mean (or sum) between the variables;
- ⇒ the distribution of the mean values will be Gaussian.
- * $Q(x)$ should be well defined.

Illustration:

- > Parabolic $Q(x)$;
- > Gaussian is shown for $\mu = 0.75$ and $\sigma = \sigma(N)/\sqrt{N}$;
- > Requires $N = 20$ to obtain Gaussian distribution.
- > Try it yourselves!

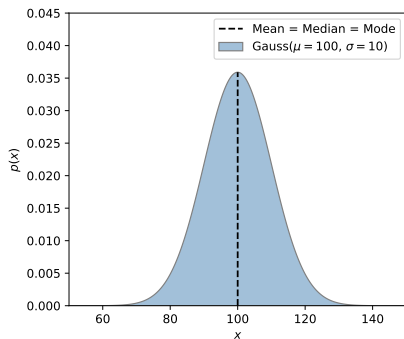


A few extra comments on distributions

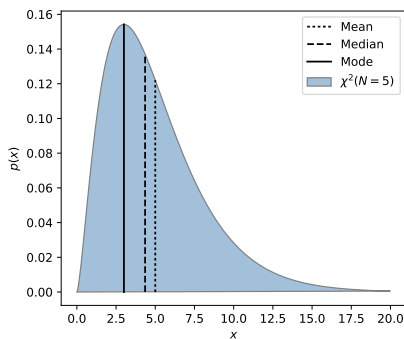
Other characteristics,

- > Mode (most-probable value)
- > Median (or more generally k -quantiles)

Symmetric



Non-symmetric



Have not mentioned so far,

- > continuous or discrete distributions;
- > cumulative distributions.



Parameter and uncertainty estimation

Parameter estimation - least square fit

Data: $x_i, y_i \pm \sigma$, Theory: $y = ax + b$.

- > Parameter determination.
- > Goodness of fit.

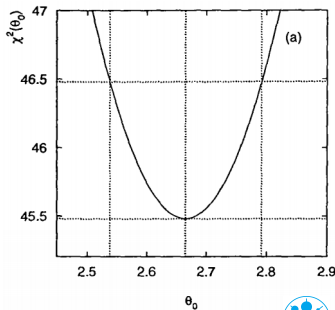
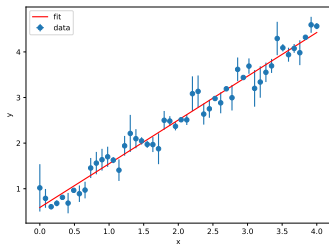
Least square fit

$$\chi^2 = \sum_i \left(\frac{(ax_i + b) - y_i}{\sigma} \right)^2$$

- * not really χ^2 (convention).
- > Linear \Rightarrow minimize analytically
$$a = \frac{\sum_i (x_i - \langle x \rangle)(y_i - \langle y \rangle)}{\sum_i (x_i - \langle x \rangle)^2}$$
$$b = \langle y \rangle - a \langle x \rangle$$
- * When $\sigma \rightarrow \sigma_i$, perform numerically, assuming normally distributed uncertainties.

Uncertainties

- > with enough data, χ^2 usually parabolic;
- > $\sigma_{\theta}^2 = 2 / (d^2 \chi^2 / d\theta^2)$
- > scan parameter space for
$$\chi^2(\theta) = \chi^2_{\min}(\theta_{\text{best}}) + 1;$$



Uncertainties

Suppose $\text{result/theory} = 0.970$, does the theory describe the data?



Uncertainties

Suppose $\text{result/theory} = 0.970$, does the theory describe the data?

0.970 ± 0.05

0.970 ± 0.005

0.970 ± 0.5



Uncertainties

Suppose result/theory = 0.970, does the theory describe the data?

$$0.970 \pm 0.05$$

$$0.970 \pm 0.005$$

$$0.970 \pm 0.5$$

Statistical uncertainties

- > Random in nature.
- > Fluctuates independently per measurement.
- > Unavoidable.
- > Usually, more data \rightarrow lower uncertainty ($\propto \sqrt{N}$).
- > e.g., counting statistics, electronic noise, etc.

Systematic uncertainties

- > Usually originate in the instrument.
- > Bias the data by unknown \sim constant offset.
- > Hard to detect, correct for, estimate.
- > e.g., miscalibration, diff. between data and simulation, simulation statistics, etc.

$$\sigma(\text{tot.}) = \sigma(\text{stat.}) \oplus \sigma(\text{syst.})$$

- > Report uncertainties separately (sometimes diff. syst. contributions).
- > Pick your battles.
- > Take into account theoretical uncertainty.



Uncertainty propagation

Assume $y = f(x) \Rightarrow \sigma_y = \left. \frac{df(x)}{dx} \right|_{x=\bar{x}} \cdot \sigma_x$

> Taylor expansion approximation, small uncertainty.

With more variables, $f(x_1, x_2, \dots, x_N)$, take correlation into account

$$\sigma_y^2 = \sum_{i,j}^N \left. \frac{\partial f}{\partial x_i} \frac{\partial f}{\partial x_j} \right|_{x=\bar{x}} \cdot V_{x_i, x_j}$$

- > V_{x_i, x_j} is the covariance of x_i, x_j (see later).
- > Correlated variables lead to increased uncertainty.
- > Opposite for anti-correlated.

examples

- > $y = x_1 - x_2 \Rightarrow \sigma_y^2 = \sigma_{x_1}^2 + \sigma_{x_2}^2 - 2 \cdot V_{x_1, x_2}$.
- > $y = x_1^\alpha \cdot x_2^\beta$, fractional uncertainties are useful (uncorr.)
 $\Rightarrow \left(\frac{\sigma_y}{y}\right)^2 = \left(\alpha \frac{\sigma_{x_1}}{x_1}\right)^2 + \left(\beta \frac{\sigma_{x_2}}{x_2}\right)^2$.
- > Sometimes easier numerically (uncorr.)

$y_1 = f(x_1 + \sigma_{x_1}, x_2, \dots, x_N)$, $y_2 = f(x_1, x_2 + \sigma_{x_2}, \dots, x_N)$, etc.

$$\sigma_y^2 = (y - y_1)^2 + (y - y_2)^2 + \dots + (y - y_N)^2.$$

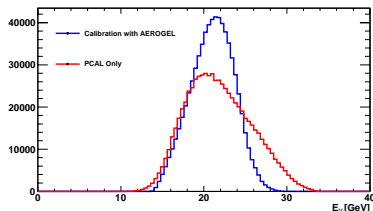
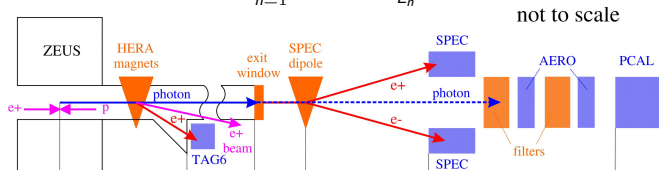


Quick examples - LS

Calibrate detectors

- > $E_\gamma = \alpha_1 \cdot E_{\text{AERO}_1} + \alpha_2 \cdot E_{\text{AERO}_2} + \alpha_3 \cdot E_{\text{PCAL}}$
- > obtain E_γ from beam energy and other calibrated detector.
- > for all data available, minimize

$$\chi^2 = \sum_{n=1}^N \frac{(\sum_{j=1}^3 \alpha_j E_{j,n} - E_n^\gamma)^2}{\sigma_{E_n^\gamma}^2}$$



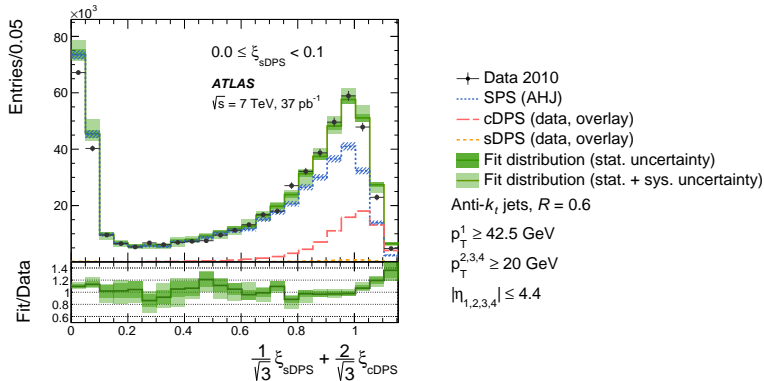
Quick examples - LS

Estimate contributions from signal/background,

- > minimize to get optimal relative fractions

$$\mathcal{D} = (1 - f)\mathcal{H}_1 + f\mathcal{H}_2$$

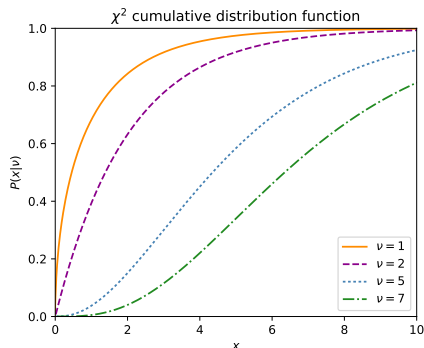
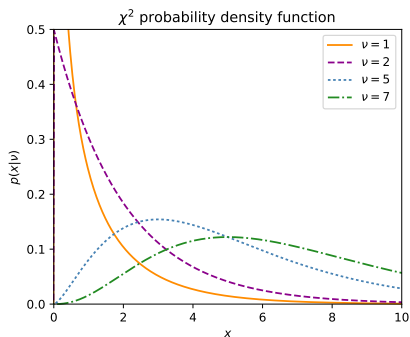
- > both model and data are binned and have uncertainties
- ⇒ can only be done numerically (ROOT, Minuit).



Goodness of fit

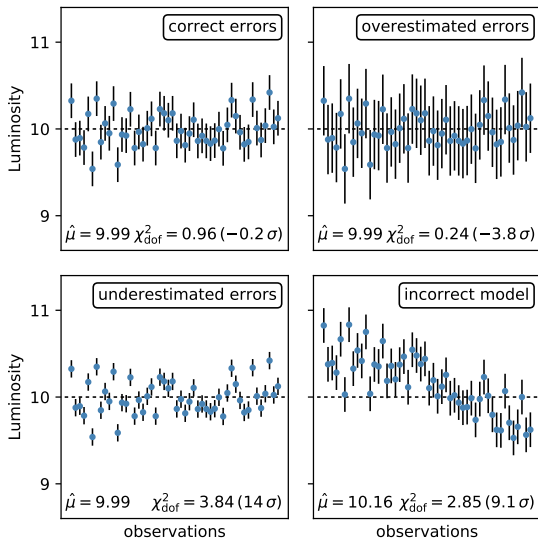
In the least squares case, straightforward

- determine χ_{\min}^2 and number of degrees of freedom, $\nu = n - p$;
- check probability based on χ^2 distribution (`TMath::Prob(chi2, ndf)`).
 - * usually referred to as p-value, prob. to find $\chi^2 > \chi_{\min}^2$ (see later)
- Rule of thumb, $\chi_{\text{dof}}^2 = \chi^2 / \nu \approx 1$.



Quick example - goodness of fit

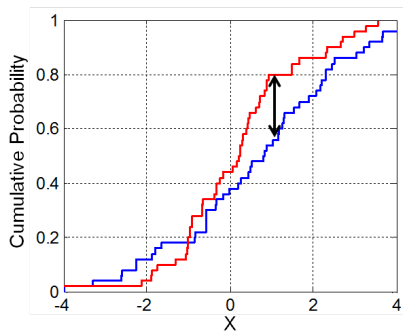
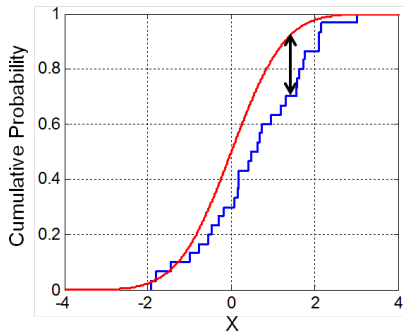
Check if brightness of star varies with time



Kolmogorov–Smirnov test

Test if distributions originate from the same underlying PDF.

- Search for largest difference between cumulative distributions.
- Useful with small amounts of data (can be used as goodness of fit).
- Fast, non-parametric, sensitive to differences in location and shape of cumulative distributions.
- Example - automatic testing of simulation output distributions.



* χ^2 also available



Probability: Bayesian vs Frequentist

Brief intro to probability

Axioms (Kolmogorov):

- > $P(A) \in \mathbb{R}$, $P(A) \geq 0$, $\forall A \in \Omega$ (Ω is the event space).
- > $\int_{\Omega} P(A) dA = 1$, i.e., Unitarity, prob. that at least one event will occur is 1.
- > if $P(A \cap B) = 0$, then $P(A \cup B) = P(A) + P(B)$.

Conditional probability:

- > $P(A|B) = \frac{P(A \cap B)}{P(B)}$

Frequentist

- > How likely is an event to occur, based on many repeatable trials.
- > Not applicable to a single event.
- > Objective statement.

$$P(A) = \lim_{n_{\text{trials}} \rightarrow \infty} \frac{n_A}{n_{\text{trials}}}$$

Bayesian

- > A “degree of belief” that an event will happen.
- > Includes previous knowledge in it (prior).

Bayes theorem - $P(A|B) = \frac{P(B|A) P(A)}{P(B)}$



Bayesian vs Frequentist

Frequentist

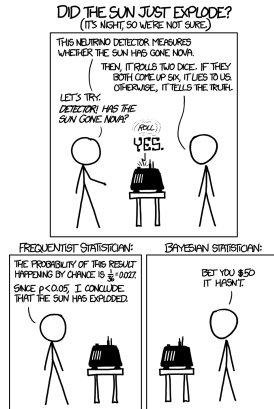
- ⇒ Probability of data given a model, $P(\text{data}|\text{model})$.
- * “Frequentist statistics gives the probability to observe data under a given hypothesis, it says nothing about the probability of the hypothesis to be true”.

Bayesian

- ⇒ Probability of model given data, $P(\text{model}|\text{data})$.
- > $P(\text{model}|\text{data}) \propto P(\text{data}|\text{model}) \times P(\text{model}) \leftarrow \text{prior}$.
- could be previous measurements;
- might be subjective;
- functional form not always known (necessary?);
- what if there is no knowledge?

Prior examples

- > Physics is “smooth”.
- > mass squared of neutrino.
- > “extraordinary claims require extraordinary evidence”.

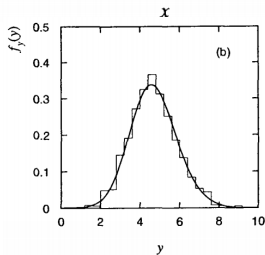
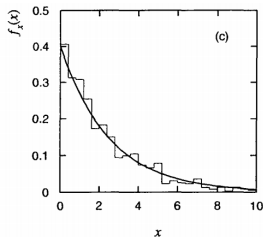
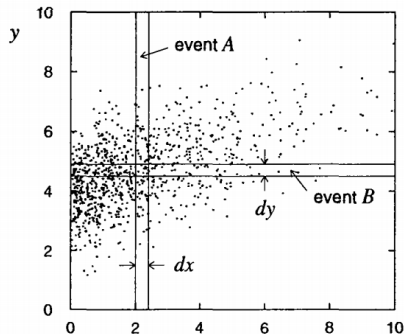


Covariance and correlation

Covariance and correlation

Consider measurements depending on more than one variable (observable).

- > What is prob. for A **and** B?
- > $P(A) = \int f(x)dx$, $P(B) = \int f(y)dy \Rightarrow P(A \cap B) = \int f(x,y)dxdy$.
- > The joint prob. $f(x,y)$ corresponds to the density of points ($N \rightarrow \infty$).
- > If not interested in y dependence \rightarrow project.
- * Profiling (see later)



Covariance and correlation

How correlated are x and y ?

⇒ Covariance

> Following the definition of 1D variance,

$$V(x) = \sigma_x^2 = E[(x - \langle x \rangle)^2] = E[x^2] - (E[x])^2;$$

> $C(x, y) = V_{x,y} = E[(x - \langle x \rangle)(y - \langle y \rangle)] = E[xy] - E[x]E[y]$.

If x and y uncorrelated,

> $P(A \cap B) = P(A) \cdot P(B)$.

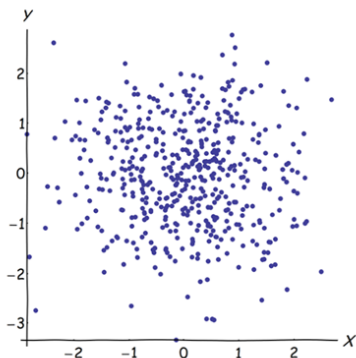
> $f(x, y) = f(x) \cdot f(y)$.

Remember uncertainty propagation?

with $y = f(x)$

$$\sigma_y^2 = \sum_{i,j} \frac{\partial f}{\partial x_i} \frac{\partial f}{\partial x_j} \Big|_{x=\bar{x}} \cdot V_{x_i, x_j}$$

notice $C = V_{x_i, x_j}$ is covariance matrix.



Covariance and correlation

The dimensionless Pearson's correlation coefficient

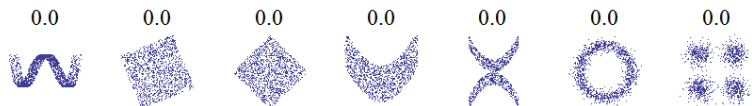
$$\rho_{x,y} = \frac{C(x,y)}{\sigma_x \sigma_y}$$



* does not measure slope.



* Test **linear** correlation/anti-correlation. Always plot your data!

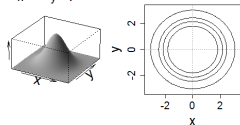


Example - 2D Gaussian

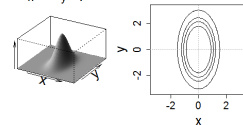
$$P(\vec{x}) = \frac{1}{2\pi\sqrt{\det(C)}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T C^{-1}(\vec{x} - \vec{\mu})\right)$$

$$\text{for } \vec{x} = (x, y) \Rightarrow C = \begin{pmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{pmatrix} = \begin{pmatrix} \sigma_x^2 & V_{x,y} \\ V_{x,y} & \sigma_y^2 \end{pmatrix}$$

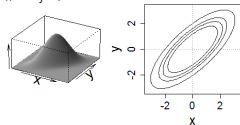
$$\sigma_x = \sigma_y, \rho = 0$$



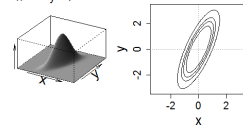
$$2\sigma_x = \sigma_y, \rho = 0$$



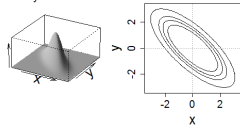
$$\sigma_x = \sigma_y, \rho = 0.75$$



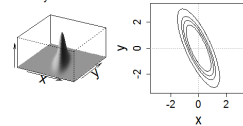
$$2\sigma_x = \sigma_y, \rho = 0.75$$



$$\sigma_x = \sigma_y, \rho = -0.75$$



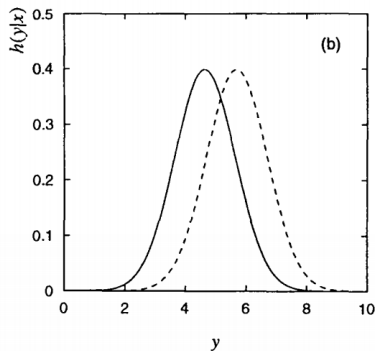
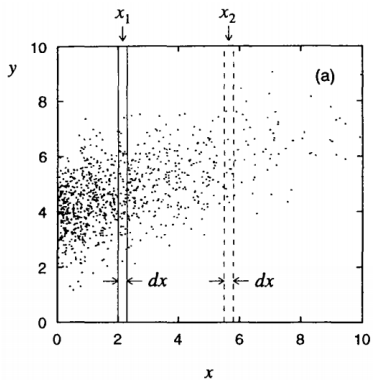
$$2\sigma_x = \sigma_y, \rho = -0.75$$



Covariance and correlation

How to deal with correlated variables?

- > If one of the variables is not used or cannot measure \rightarrow project.
- > Bin the data (profiling), issues with this method?



- > Variable transformation.

Principal component analysis

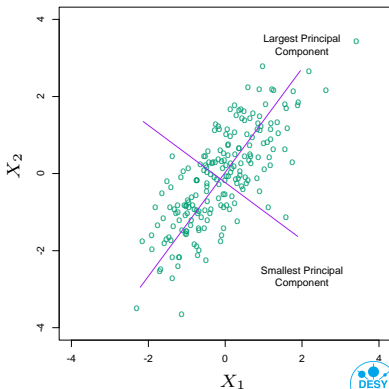
Perform orthogonal linear transformation, each component (variable) maximizes variance.

Process (X is data matrix),

- > diagonalize the $X^T X$ matrix, calculate eigenvectors and eigenvalues;
- > the (ordered) eigenvectors are the new observables;
- > the variance “score” is given by the eigenvalues.

Some comments

- > Covariance, $C \propto X^T X$.
- > First n components embody majority of information.
- ⇒ Can be used to reduce dimensionality.
- > Often one of the first steps in multi-variate analysis.
- > Useful only for linearly correlated variables (non-linear options available).
- > Various tools available (ROOT, scikit-learn, R).

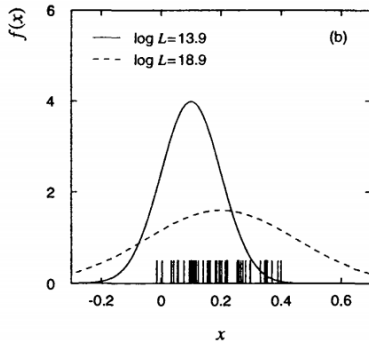
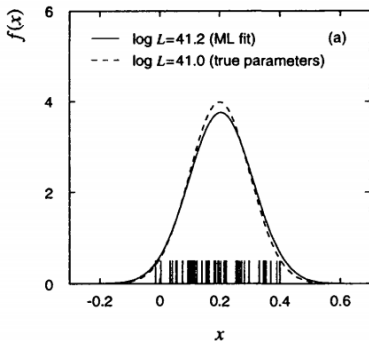


Hypothesis testing

Parameter estimation - Maximum likelihood

Maximum likelihood for parameter determination.

- Assume we observe N **independent** events, y_i .
- The hypothesis to check has a PDF, $p(y, \theta)$, where θ is param.
- Events are independent, combine prob as $\mathcal{L}(\theta) = \prod_i^N p(y_i, \theta)$.
- ➔ calculate $\mathcal{L}(\theta)$ for all θ values (fixed y_i).
- $\mathcal{L}(\theta)$ is at maximum when $\theta = \theta_{\text{true}}$.



Maximum likelihood

Conventional to instead minimise $-2 \cdot \ln \mathcal{L}(\theta)$

> $\ln \mathcal{L}(\theta) = \sum_i^N p(y_i, \theta)$ (numerically easier).

Confidence interval

> $\ln \mathcal{L}(\theta_0 \pm \sigma) = \ln \mathcal{L}(\theta_0) - 1/2$ (also $\frac{d^2 \ln \mathcal{L}(\theta)}{d\theta^2}$).

> For $-2 \cdot \ln \mathcal{L}(\theta) \rightarrow -2 \cdot \Delta \ln \mathcal{L}(\theta) = 1$.

When $\mathcal{L}(\theta)$ is \sim Gaussian

\Rightarrow confidence interval of $\sim 68\%$ for θ .

> could be asymmetric.

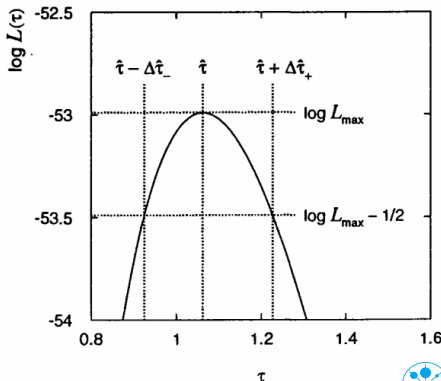
If $\mathcal{L}(\theta)$ "very" non-Gaussian

\Rightarrow revert to Neyman confidence interval (will not cover).

Goodness of fit

> Not straightforward, at large N
 $-2 \cdot \Delta \ln \mathcal{L}(\theta) \rightarrow \chi^2$
(Wilks' theorem).

> Toy Monte Carlo.



Quick example - MLE

Lifetime determination (L. Lyons)

- > Radioactive decay, $\frac{dn}{dt} = \frac{1}{\tau} e^{-\frac{t}{\tau}}$; (normalization, $\frac{1}{\tau}$).
- > Observed decays $t_i = t_1, t_2, \dots, t_N$.
- * neglecting background, time smearing, etc.

Construct likelihood

$$> \mathcal{L}(\tau) = \prod_i^N \left(\frac{dn}{dt}\right)_i = \prod_i^N \frac{1}{\tau} e^{-\frac{t_i}{\tau}}.$$

$$> \ln \mathcal{L}(\tau) = \sum_i^N \left(-\frac{t_i}{\tau} - \ln \tau\right).$$

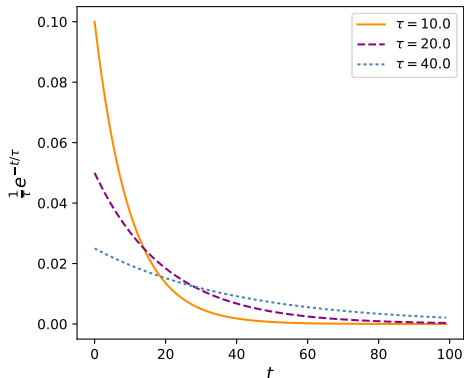
$$> \frac{d \ln \mathcal{L}(\tau)}{d\tau} = \sum_i^N \left(\frac{t_i}{\tau^2} - \frac{1}{\tau}\right) = 0.$$

$$\Rightarrow \tau = \sum_i^N \frac{t_i}{N} = \langle t_i \rangle.$$

Uncertainty estimation

$$> \frac{d^2 \ln \mathcal{L}(\tau)}{d\tau^2} = -\sum_i^N \left(\frac{2t_i}{\tau^3} + \frac{1}{\tau^2}\right) = 0.$$

$$\Rightarrow \sigma_\tau = \frac{\tau}{\sqrt{N}} \text{ (notice } \frac{1}{\sqrt{N}} \text{ dependency).}$$



Hypothesis testing

Use likelihood for hypothesis testing, often formulated as

- > Null hypothesis, H_0 , (e.g., Standard Model only).
- > Alternative hypothesis, H_1 (e.g., Standard Model + new physics).

Simple hypothesis

Calculate $\mathcal{L}(H_0(\theta))$

- > decide if data is likely for H_0 (p -value).
- > If not, claim discovery (of what?)
- Existence of a particle (Higgs, new particle)
- A new γ -ray source.

Composite hypothesis

compare $\mathcal{L}(H_0(\theta))$ and $\mathcal{L}(H_1(\theta))$.

- > Usually likelihood ratio is used.
- > More sensitive to H_1 .
- > Based on p -values, which H_i is more likely.
- Particle with certain mass, width, coupling constants.
- Position and spectra of γ -ray source.



Hypothesis testing - exclude H_0

Types of errors:

- > False positive (Type-1 error): wrongly reject H_0 (no new physics).
- > False negative (Type-2 error): wrongly accept H_0 (missed new physics in data).

		True State of Nature	
		H_0 is true	H_0 is false
Our Decision	Do not reject H_0	Correct decision	Type II error
	Reject H_0	Type I error	Correct decision

Define the probabilities

- > Type-1 error rate (significance α)

$$\alpha = \int_{x \geq x_0} p(x|H_0) dx$$

i.e., probability of the data given H_0 (familiar?).

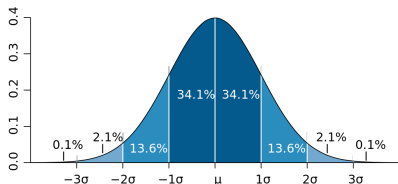
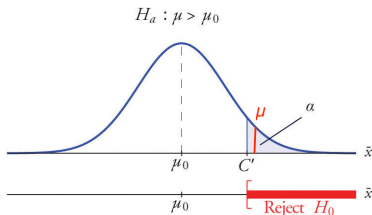
- relation to p -value in next slides.



Hypothesis testing - exclude H_0

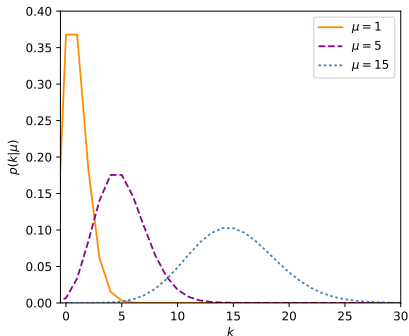
Gaussian example

- > Assume PDF is Gaussian distributed around μ_0 and we measure μ .
- > The p -value is the probability to measure μ or higher.
- > α is the probability to measure C' or higher.
- > Compare p -value to α , decide to accept/exclude H_0 .

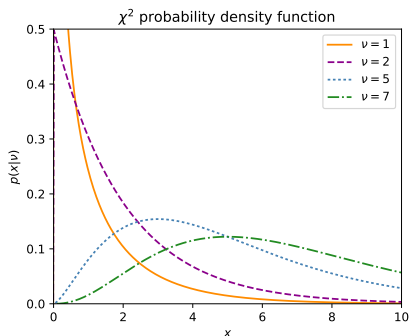


- > One-sided p -value (or α) at $5\sigma = 3 \cdot 10^{-7}$.
- > Sometimes both tails need to be taken into account ($\alpha/2$).
- * See relation to goodness of fit?

p-values not only for Gaussian distributions



$$P(\mu = 5, n \geq 13) = 0.001$$



$$P(\nu = 5, x \geq 20.5) = 0.001$$

Convention

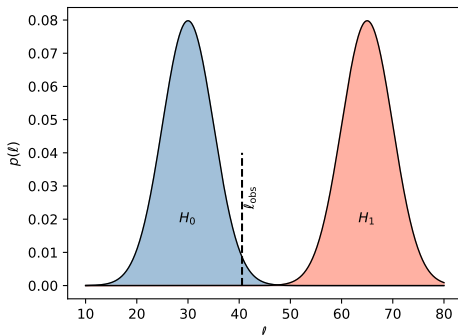
- > Convert p -value from any PDF to equivalent one-sided Gaussian σ .
- > Does not mean PDF is Gaussian, simply easier to remember.
- > p -value is $P(\text{data}|H_0)$, it is **not** $P(H_0|\text{data})$.

Hypothesis testing

For comparing H_0 & H_1 , **Neyman-Pearson Lemma**

⇒ Likelihood ratio test is optimal discriminant (assuming no free parameters).

- Log Likelihood ratio $\ell = -2 \ln \left(\frac{\mathcal{L}(\text{data}, H_1)}{\mathcal{L}(\text{data}, H_0)} \right)$.
- If $H_i(\theta)$, use simulation to generate distributions of ℓ for H_i .
- Take measurement and calculate ℓ after maximizing \mathcal{L} for both $H_i(\theta)$.
- Calculate both p -values, decide which H_i to accept.



* More complicated in reality.



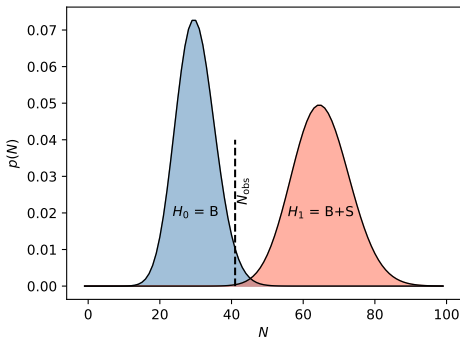
Exclusion limit (simplified)

Assume $H_0 = \text{background (SM)}$ and $H_1 = \text{background} + \text{signal}$.

- > Number of events (cross-section) observed is Poisson distributed.
- > From p -values, accept H_0 .

Set limit

- > Find the maximum signal strength for which $p(H_1) < 5\%$.
- > Set limit on signal at 95% confidence level (exclusion, 2σ).

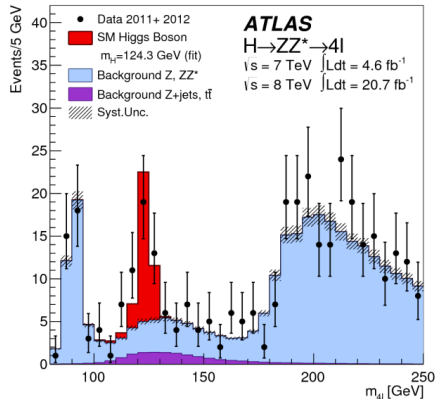
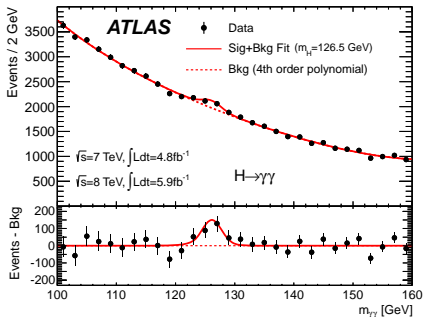


- * Usually based on the likelihood ratio test statistics.



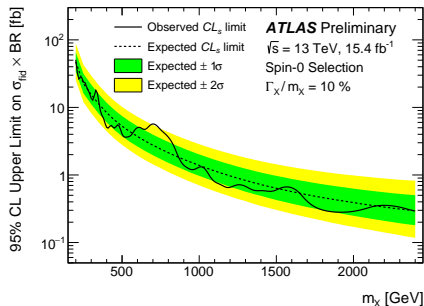
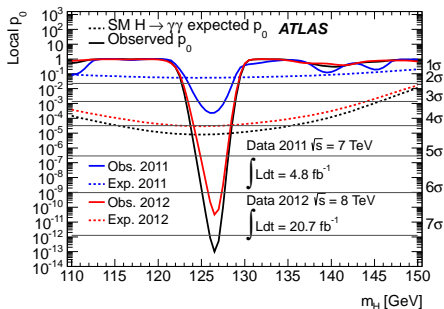
Higgs discovery

- Visible bump in the data.
- For $H \rightarrow \gamma\gamma$, background fitted with a smooth distribution.
- Complicated background in $H \rightarrow 4\ell$.



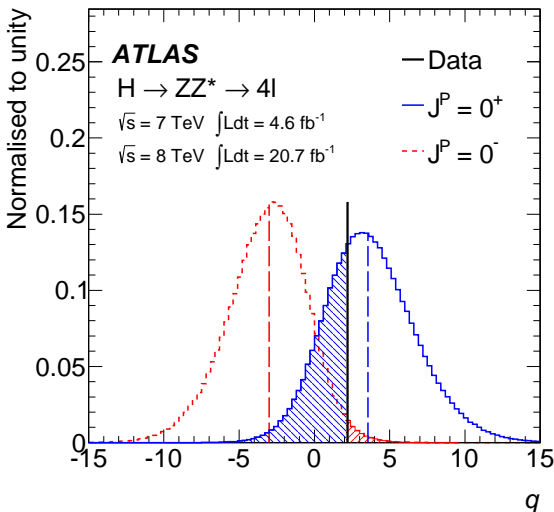
Discovery/Exclusion

- local p -value of observed Higgs signal (signal stronger than expected).
- Search for massive scalar decaying to two γ , not found
- ➔ set an upper limit on the cross-section (\times branching ratio).



Higgs spin

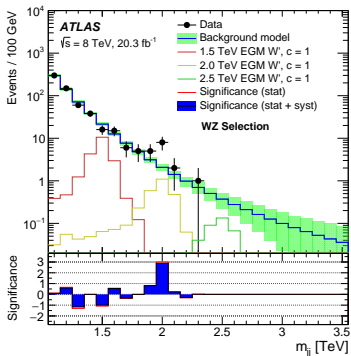
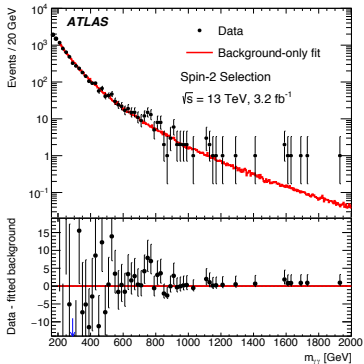
- > Use likelihood ratio $q = -2 \ln \left(\frac{\mathcal{L}(\text{data}, 0^+)}{\mathcal{L}(\text{data}, 0^-)} \right)$ to determine Higgs spin.



Look elsewhere effect

Bump hunting? Peaks can be anywhere!

- Increase p -value to take into account (quote local and global p -value).
- Correction roughly width mass interval divided by width particle.
- Confirmation from other experiment is crucial.
- * Consider amount of searches at any given time.



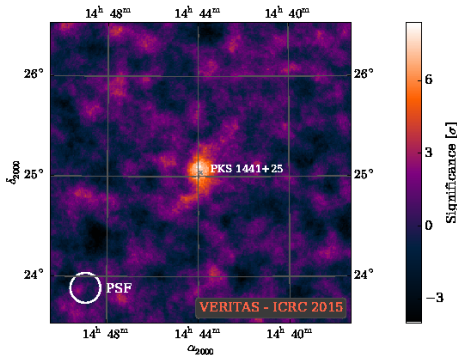
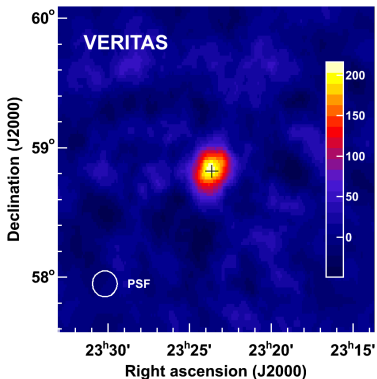
- * Remember the track with 110 bubbles?



Look elsewhere effect

Also in searches for γ -ray sources

- * Usually referred to as trials factor.
- > Include also cuts in the correction (not always easy).



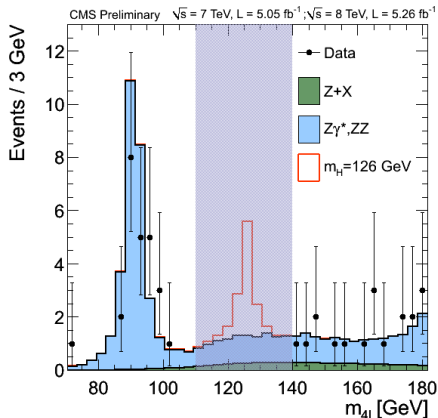
Blind analysis

R. Feynman

The first principle is that you must not fool yourself — and you are the easiest person to fool

Whenever possible, perform blind analysis

- > Keep the “signal box” closed.
- > Construct and refine analysis on simulation, cannot change after unblinding.
- > Use only part of the data available.



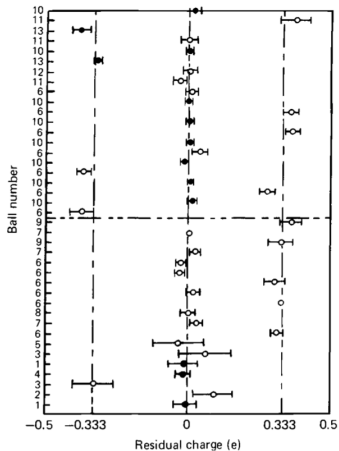
Blind analysis

R. Feynman

The first principle is that you must not fool yourself — and you are the easiest person to fool

Whenever possible, perform blind analysis

- > Keep the “signal box” closed.
- > Construct and refine analysis on simulation, cannot change after unblinding.
- > Use only part of the data available.
- > Add random numbers to results.
- > Use fake signal to test procedure (done at LIGO).



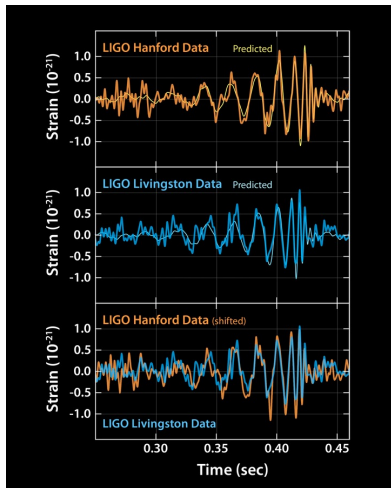
The 5σ criteria

Probability of fluctuation of 5σ is less than 1 in a million, tiny!

- > This was not always the case (and is not in other fields).
- > A lot more data these days.
- > Sometimes hard to estimate look elsewhere effect.
- > Underestimated systematic uncertainties?
- > A discovery of new physics will be a game changer, better not take it back.

Bayesian prior

extraordinary claims require extraordinary evidence



Monte Carlo methods

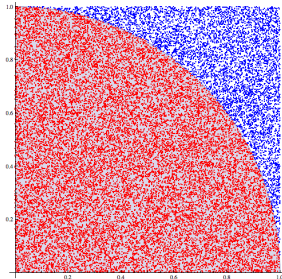
Monte Carlo methods

Wikipedia: “computational algorithms that rely on repeated random sampling to obtain numerical results.”

Useful for, e.g.,

- > Numerical integration.
- > Simulating particle interactions or decay.
- > Uncertainty estimation.

Example: estimate π



```
from random import random
from math import sqrt, pi
inside=0
n=1000000
i_print = [1, 10, 100, 1000, 10000, 100000, 1000000]
for i in range(0,n+1):
    x=random()
    y=random()
    if sqrt(x*x+y*y)<=1:
        inside+=1
    if i in i_print:
        piNow=4*inside/i
        print ('pi(i=%d) = %.4f, error = %.4f' % (i, piNow, abs(piNow - pi)))
```

```
pi(i=1) = 4.0000, error = 0.8584
pi(i=10) = 3.6000, error = 0.4584
pi(i=100) = 3.3600, error = 0.2184
pi(i=1000) = 3.1240, error = 0.0176
pi(i=10000) = 3.1264, error = 0.0152
pi(i=100000) = 3.1433, error = 0.0017
pi(i=1000000) = 3.1402, error = 0.0014
```

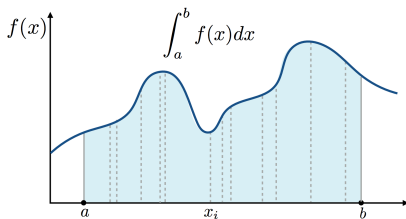
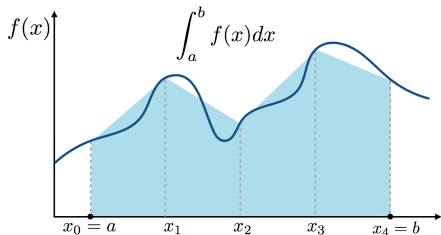
Monte Carlo integration

Simple numerical integration

- > Divide range to small pieces of known area and sum.
- > Suffers from curse of dimensionality, $N_{\text{calc}} = n^d$.

Similar to π estimate example, can sample function at random points.

- > Avoids curse of dimensionality of numerical integration, error $\propto 1/\sqrt{N}$.
- > Works for any function (including discontinuous ones).
- > Faster at large d .
- > Used in e.g., phase-space integration of matrix elements.

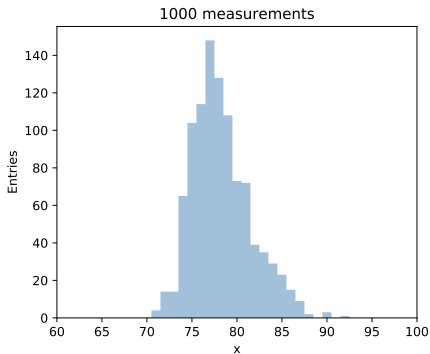
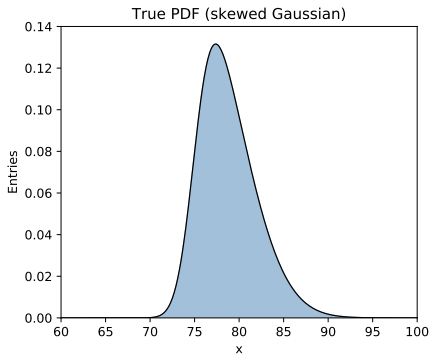


Bootstrap method

Assume N measurements of x , x_i , how to estimate $\mu_x \pm \sigma_{\mu_x}$?

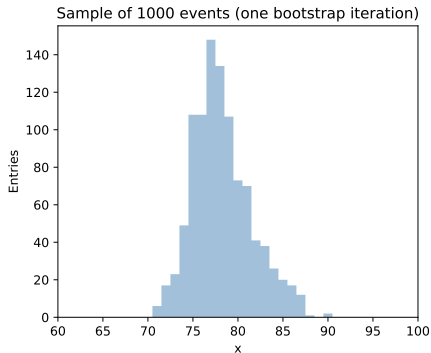
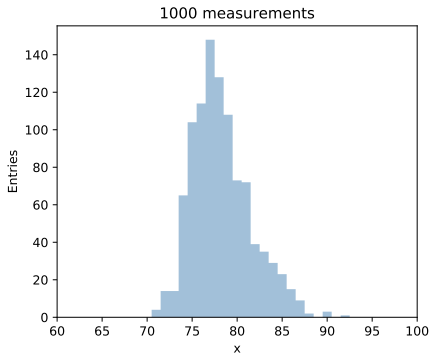
Not easy to estimate σ_{μ_x} without knowing PDF of x .

- > Usually there is no access to the “true” PDF.
- ⇒ The distribution of x_i is best approximation of it.



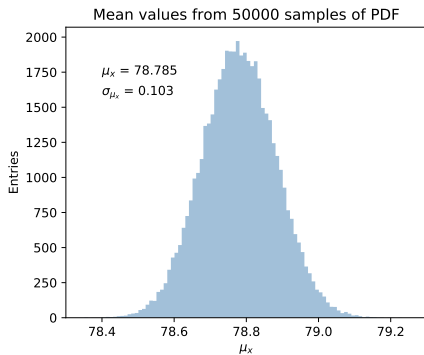
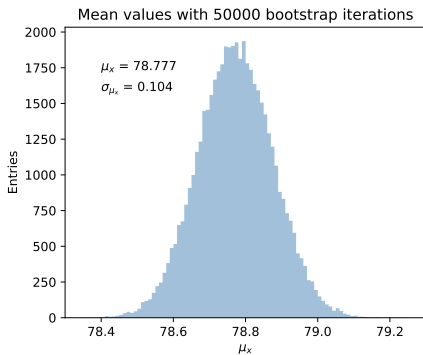
Bootstrap method

- > Can generate “new” measurements by sampling from x_i .
- > Each iteration sample events from the 1000 measurements, allowing repetition.
- > Calculate μ_x for “new” distribution.



Bootstrap method

- > Obtain a distribution of μ_x by repeating 50,000 times.
- > For comparison, perform 50,000 experiments using true PDF, each with 1000 events.
- ⇒ σ_{μ_x} from bootstrap reproduces that from independent experiments.



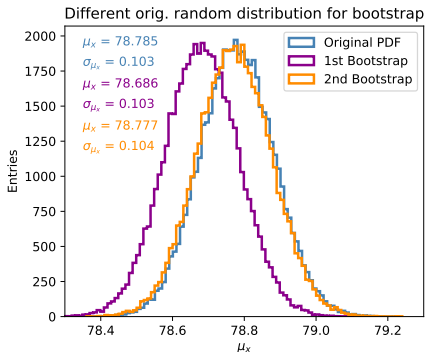
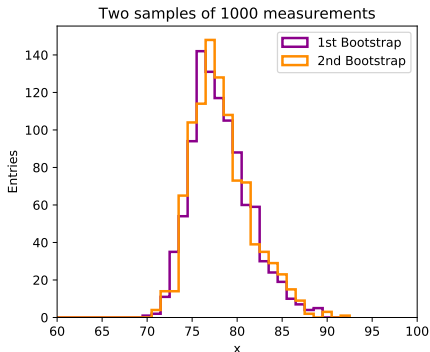
- * Toy MC
- * Can be used in numerical estimation of uncertainties



Bootstrap method

While making the plots, encountered interesting case,

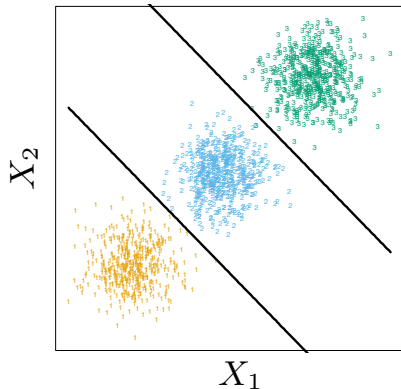
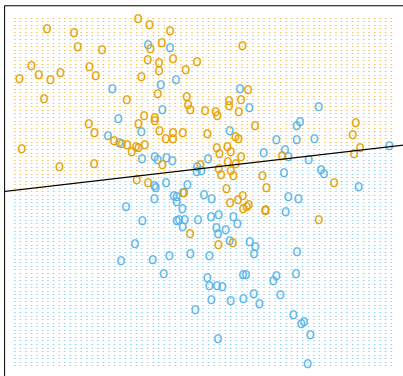
- > In 1st trial, saw a bias between μ_x distributions (not significant, but still).
- > Spread was OK \rightarrow test by changing random seed when performing first “measurement” of 1000 events.
- > With different random seed, no more bias and same σ_{μ_x} .



Event classification

Significant part of data analysis, classifying between events.

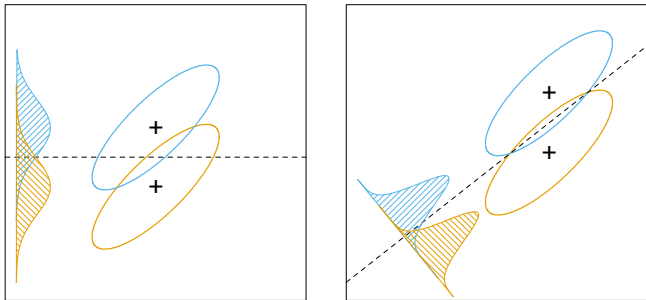
- > Define decision boundaries (cuts).
- > Requires prior information (usually from simulation).
- > Can it be done “visually”? Usually too many observables/classes.



Event classification

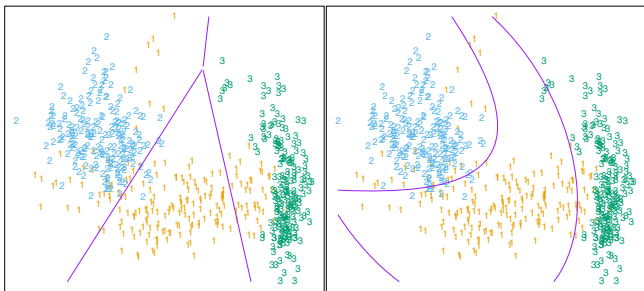
Various ways to deal with it (see 3rd lecture about machine learning)

- > If observables not highly correlated, can define cuts in bins.
- > Many algorithms available to optimize cuts (e.g., linear discriminant analysis, kNN, SVM, BDT, ANN).
- LDA is similar to Principal Component Analysis, but it maximizes separability between event classes.
- Maximizes distance between means and minimizes overlap.
- Can be used to reduce dimensionality and optimize cut hyperplane.



Event classification

- > Use data with known labels to train discriminant, apply later to “real” data.
- > Can expand space to $5d = X_1, X_2, X_1 \cdot X_2, X_1^2, X_2^2$ to obtain non-linear hyperplanes using linear method.



- * Transformed observables useful also for non-linear methods (e.g., $\log E$).
- * Take care when using “automatic” classifiers, study results carefully.
- * Consider systematic uncertainties when selecting observables.

Miscellaneous

What is unfolding?

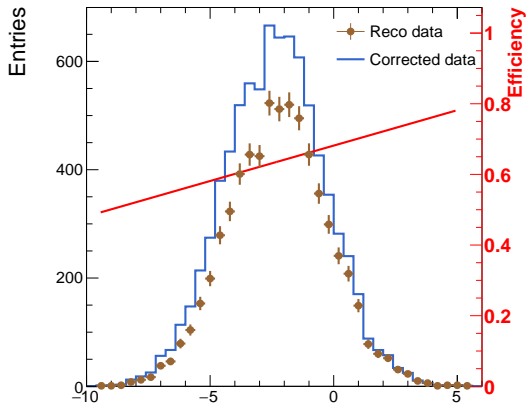
The process of correcting the data for detector effects

A measured distribution is affected by

- > Inefficiencies in the detector → lost events.
- > Bias → if $\langle x \rangle$ is true mean, measure $\langle x' \rangle = \langle x \rangle + \Delta x$.
- > Smearing → the detector has finite resolution.

Simple example,

- > known efficiency function.
- > no bias or smearing.
- ⇒ correct each bin for fractional loss of events.
- * Not really unfolding



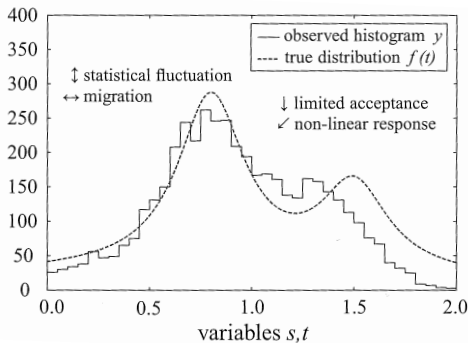
Unfolding

In practice, given a measured histogram y^{data} ,

- > want to obtain “true” distribution x^{data} , where $y^{\text{data}} = R^{\text{data}} \cdot x^{\text{data}}$.
- > The matrix R_{ij}^{data} is the response function of the detector.
- > Inefficiencies contribute to diagonal elements → **per-bin correction**;
- > bias and smearing to off-diagonal → **bin migration**.

How to derive R^{data} ?

- > In simulation we have all necessary information.
- > $y^{\text{MC}} = R^{\text{MC}} \cdot x^{\text{MC}}$, where R^{MC} is our detector simulation.
- > Assume $R^{\text{data}} = R^{\text{MC}} = R$.
- > Notice that in general,
 $y^{\text{data}} \neq y^{\text{MC}}$,
 $x^{\text{data}} \neq x^{\text{MC}}$,
but should be close.
- > Can we then simply use
 $x^{\text{data}} = R^{-1} \cdot y^{\text{data}}$?



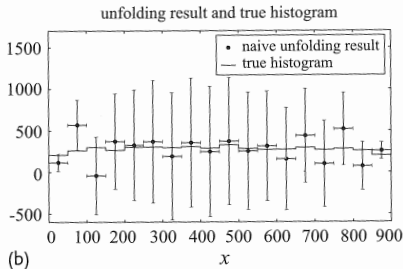
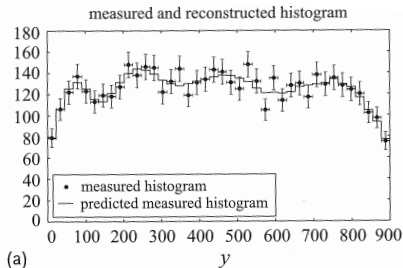
Unfolding is an ill-posed problem

- With finite statistics, naive unfolding fails.
- > Leads to significant statistical fluctuations between bins.
- Negative correlation coefficients between adjacent bins.
- Positive coefficients between next-to-nearest neighbours.

How to deal with fluctuations?

Regularization

- > Increase weight of “smoother” solutions, damp oscillations.
- > Unfold iteratively using Bayes theorem (will not cover).
- * Various tools available, e.g., RooUnfold.



Regularized unfolding

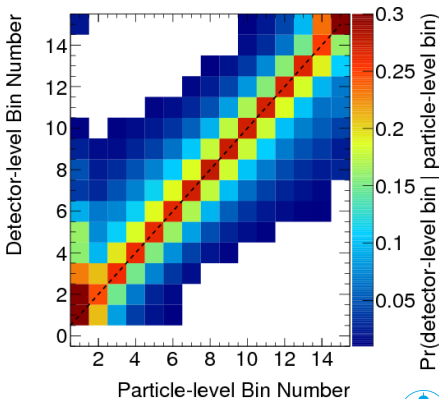
The unfolding problem can be written as a minimization of (simplified)

$$\chi^2(x^{\text{data}}) = (R \cdot x^{\text{data}} - y^{\text{data}})^T (R \cdot x^{\text{data}} - y^{\text{data}}) + \tau (Lx^{\text{data}})^T (Lx^{\text{data}})$$

L is regularization matrix (second derivative commonly used).

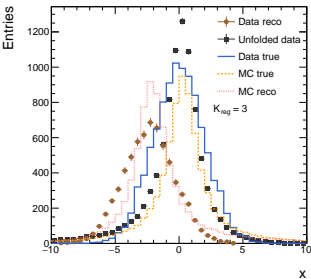
Second term dampens oscillations.

- > τ is regularization parameter,
- * if τ is too small \rightarrow oscillations;
- * if τ is too large $\rightarrow x^{\text{data}}$ too smooth and biased towards x^{MC} ;
- > Depends on number of events and binning.
- > Some trial & error to choose τ .
- > Usually chosen using (independent) MC samples.

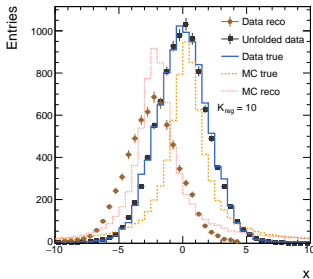


Unfolding

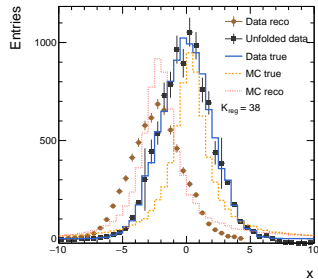
Over-regularized



Correctly-regularized



Under-regularized



* Notice, $y^{\text{data}} \neq y^{\text{MC}}$, $x^{\text{data}} \neq x^{\text{MC}}$

Why do we bother?

- Allows to compare directly to theoretical models and among experiments.
- “Future proof” the data.



Unfolding vs folding

Folding (or forward folding) is another option

- > Instead of correcting data, publish it with corresponding R .
- > The problem is then technically simpler,

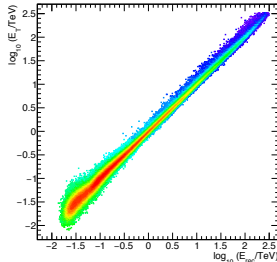
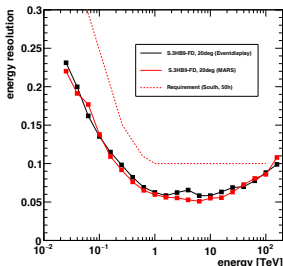
$$\chi^2(x^{\text{theo}}(\theta)) = (R \cdot x^{\text{theo}}(\theta) - y^{\text{data}})^T (R \cdot x^{\text{theo}}(\theta) - y^{\text{data}}).$$

in the case where $x^{\text{theo}}(\theta)$ is the model one wants to test.

- > Avoids unfolding issues (ill-defined problem, converting statistical uncertainties to systematic ones).

Issues with folding

- > Does not allow comparison between experiments.
- > Harder to test your model against data from various experiments.



What to do?

When possible, unfold.



Extended MLE

The production rate depends on mass of a particle, need to estimate both?

- Extended MLE (Poisson process, PDF $f(x_i; \theta)$)

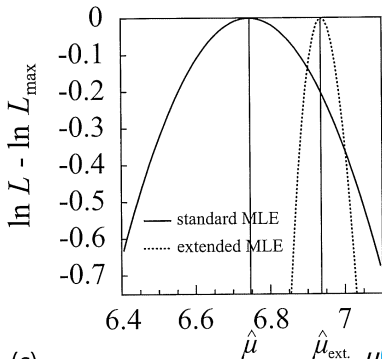
$$L(x; \nu, \theta) = \frac{\nu^N}{N!} e^{-\nu} \prod_i^N f(x_i; \theta)$$

maximize with respect to both θ and ν (profile likelihood).

- Improved precision of fitted parameters obtained if θ and ν are correlated (e.g., θ = particle mass).

Nice example in [Data Analysis in High Energy Physics book](#)

- PDF, $f(x_i; \mu) = \mathcal{G}(\mu)$.
- Parameter of interest is μ .
- Assume $\nu = 9e^{-4(\mu-7)}$.
- Simulate events with $\mu_{\text{true}} = 7$.
- Perform profile likelihood to obtain more precise $\hat{\mu}$.



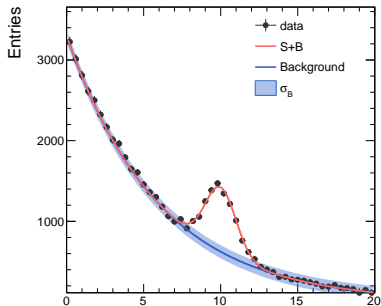
Extended MLE and nuisance parameters

Can be used to include uncertainties in likelihood fit

- > Assume signal and background contributions S and B .
- > Try to estimate S , include Gaussian uncertainty on background $B \rightarrow \theta B$,
$$\mathcal{L}(N; S, \theta) = \frac{(S+\theta B)^N}{N!} e^{-(S+\theta B)} \mathcal{G}(\theta - 1, \sigma_\theta)$$
- > Background is constrained to our best guess ($\theta = 1$), with a σ_θ spread.
- > Maximize \mathcal{L} to estimate S while marginalizing θ .

In reality can become complex

- > Estimate various parameters of S and B simultaneously (e.g., particle mass).
- > S and B affected by various uncertainties (many nuisance parameters).
- > Divide data to various regions where different uncertainties contribute.
- * Use tools to build models and perform fit, e.g., RooFit, ctools, Gammapy.



Summary

Statistics is everywhere in physics

- > Lectures can get a bit abstract → learn by doing.
- > Likely that your problem was solved already somewhere else, consult books and the web before reinventing the wheel.
- > Use software packages as much as possible (ROOT, RooFit, various Python tools, etc.)

Subjects not covered but worth reading about

- > Confidence intervals, coverage and limit setting.
- > Dealing with systematic and theory uncertainties.
- > Estimating contributions through templates and control regions.
- > Combining results.
- > Many more.

e-mail: orel.gueta@desy.de

