# **Data Analysis**

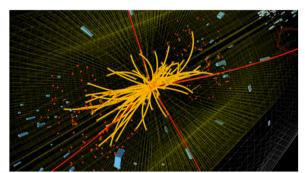
### **Ivica Puljak**

University of Split, FESB, Split, Croatia

Ivica.Puljak@cern.ch

# Starting the new era In the future, calendar of particle physics will be Before Higgs (BH) After Higgs (AH) July 4, 2012

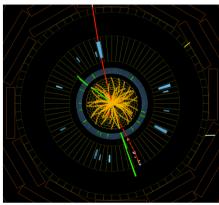
### 04.07.2012: Higgs within reach



Proton-proton collision in the CMS experiment producing four high-energy muons (red lines). The event shows characteristics expected from the decay of a Higgs boson but it is also consistent with background Standard Model physics processes (Image: CMS)

At a seminar on 4 July, the ATLAS and CMS experiments at CERN presented their latest results in the search for the long-sought Higgs boson. Both experiments see strong indications for the presence of a new particle, which could be the Higgs boson, in the mass region around 126 gigaelectronvolts (GeV).

### 01.08.2012: ATLAS and CMS submit Higgs-search papers

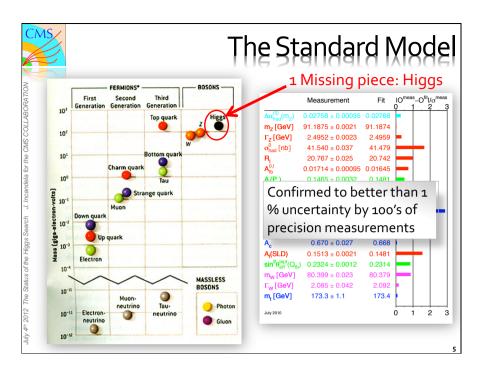


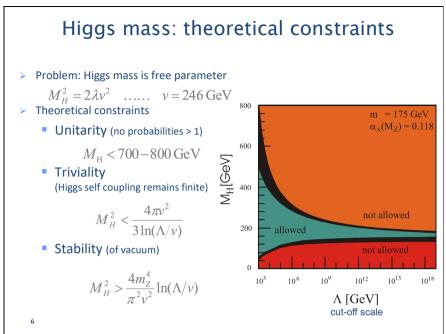
Protons collide in the CMS detector at 8 TeV, forming Z bosons which decay into electrons (green lines) and muons (red). Such an event is compatible with the decay of a Standard Model Higgs boson (Image: CMS)

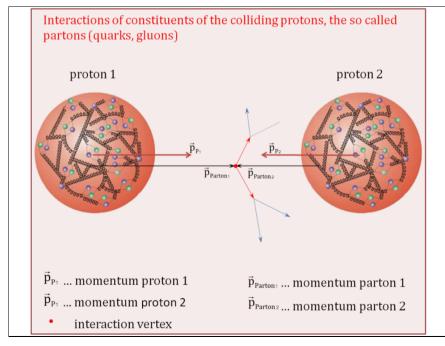
The ATLAS and CMS collaborations today submitted papers to the journal Physics Letters B outlining the latest on their searches for the Higgs boson. The teams report even stronger evidence for the presence of a new Higgs-like particle than announced on 4 July.

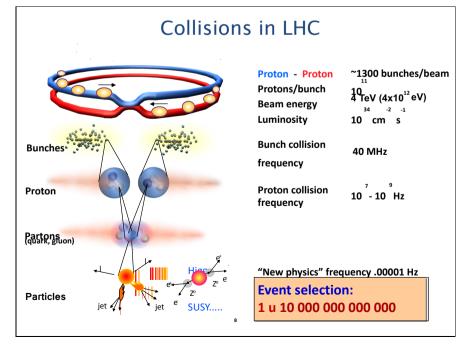
I. Puljak: Data Analysis

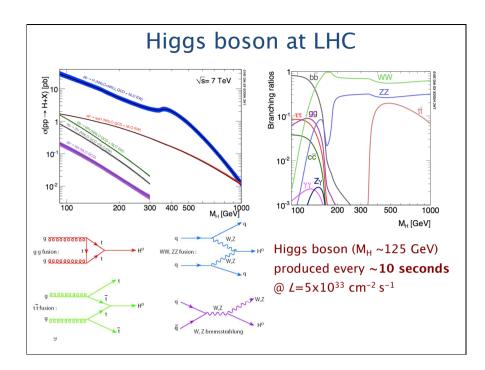
I. Puljak: Data Analysis

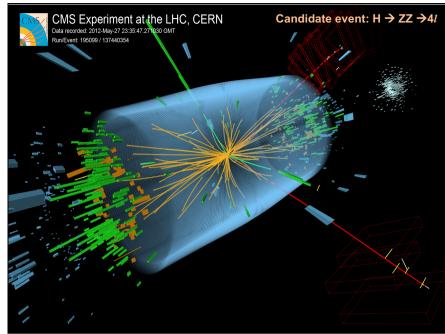


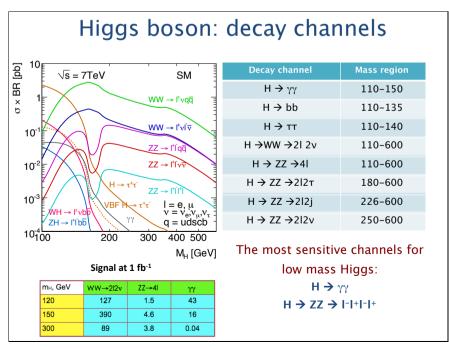


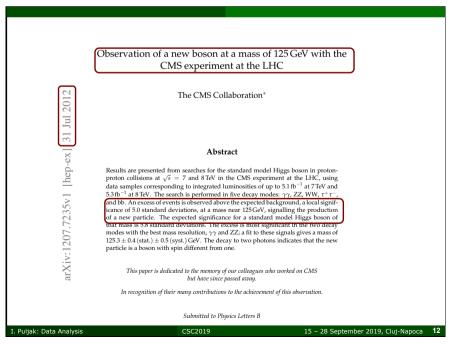












CERN-PH-EP-2012-218
Submitted to: Physics Letters B

Jul 2012

Observation of a New Particle in the Search for the Standard Model Higgs Boson with the ATLAS Detector at the LHC

The ATLAS Collaboration

### Abstract

A search for the Standard Model Higgs boson in proton-proton collisions with the ATLAS detector at the LHC is presented. The datasets used correspond to integrated luminosities of approximately 4.8 fb-1 collected at  $\sqrt{s} = 8 \, \text{TeV}$  in 2011 and 5.8 fb-1 at  $\sqrt{s} = 8 \, \text{TeV}$  in 2012. Individual searches in the channels  $H \to ZZ^{(c)} \to 4\ell$ ,  $H \to \gamma \gamma$  and  $H \to WW^{(c)} \to e \gamma \mu \gamma$  in the 8 TeV data are combined with previously published results of searches for  $H \to ZZ^{(c)}$ ,  $WW^{(c)}$ , bh and  $\tau^+ \tau^-$  in the 7 TeV data. Clear evidence for the production of a neutral boson with a measured mass of  $126.0 \pm 0.4 \, (\text{stat}) \pm 0.4 \, (\text{sys}) \, \text{GeV}$  is presented.

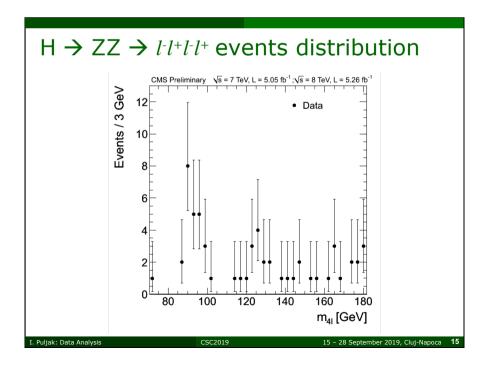
This observation, which has a significance of 5.9 standard deviations, corresponding to a background fluctuation probability of  $1.7 \times 10^{-9}$ , is compatible with the production and decay of the Standard Model Higgs boson.

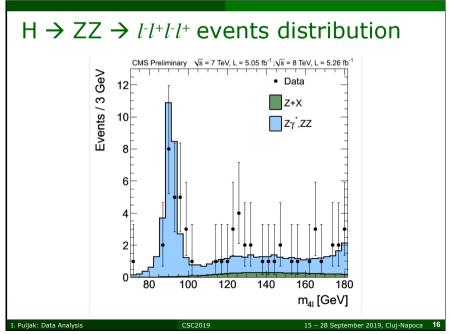
I. Puliak: Data Analysis

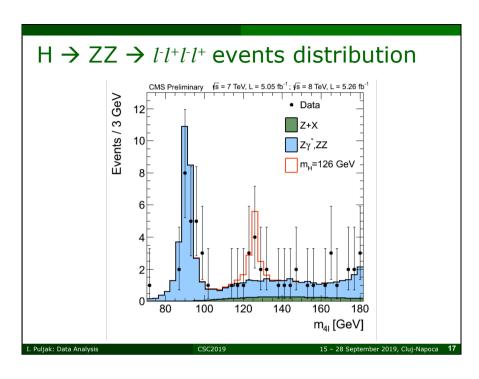
CSC201

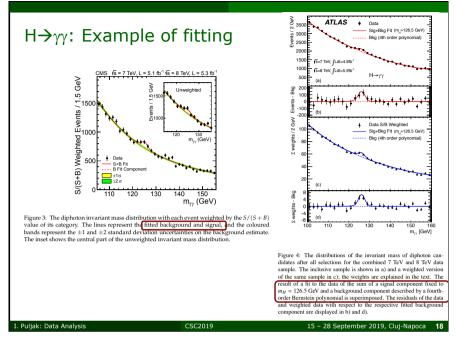
15 - 28 September 2019, Cluj-Napoca

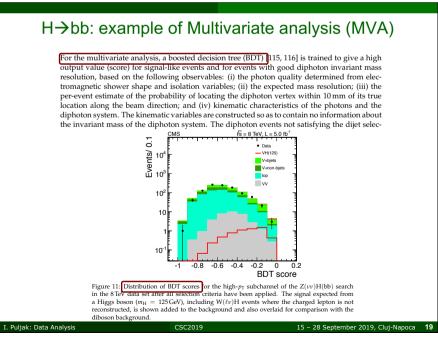
### Expectations vs measurements ATLAS $H \rightarrow ZZ^{(*)} \rightarrow 4I$ Background Z+jets, tt Signal (m<sub>H</sub>=125 GeV) W Syst.Unc. 15 L/s = 7 TeV: JLdt = 4.8 fb $\sqrt{s}=7$ TeV, L = 5.1 fb $^{\circ}$ $\sqrt{s}=8$ TeV, L = 5.3 fb √s = 8 TeV: ∫Ldt = 5.8 fb GeV ♣ Data Z+X ) 6/ study 12/ Zγ\*, ZZ m.=125 GeV 150 250 m<sub>41</sub> [GeV] Figure 2: The distribution of the four-lepton invariant mass, $m_{4\ell}$ , for the selected candidates, compared to the background expectation in the 80–250 GeV mass range, for the combination of the $\sqrt{s} = 7$ TeV and $\sqrt{s} = 8$ TeV data. The signal expectation for a SM Higgs with $m_H = 125$ GeV is also shown m<sub>4f</sub> (GeV) Figure 4: Distribution of the four-lepton invariant mass for the ZZ $\rightarrow$ 4 $\ell$ analysis. The points represent the data, the filled histograms represent the background, and the open histogram shows the signal expectation for a Higgs boson of mass $m_{\rm H}=125\,{\rm GeV}$ , added to the background expectation. The inset shows the $m_{4f}$ distribution after selection of events with

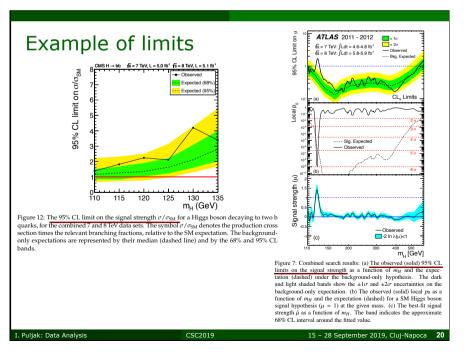


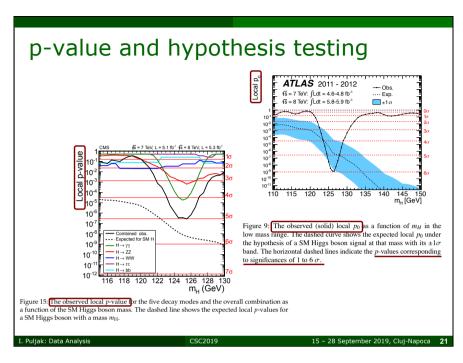


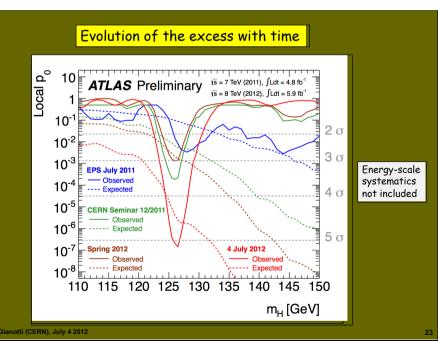






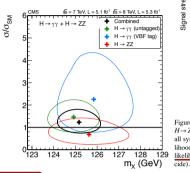






# Measuring properties

Asymptotically the test statistic 2 ln  $\lambda(\mu, m_H)$  is distributed as a  $\chi^2$  distribution with two degrees of freedom. The resulting 68% and 95% CL contours for the  $H \rightarrow \gamma \gamma$  and  $H \rightarrow WW^{(*)} \rightarrow \ell \gamma \ell \gamma$  channels are shown in



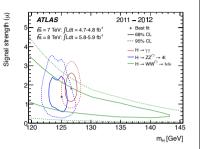


Figure 11: Confidence intervals in the  $(\mu, m_H)$  plane for the  $H \to ZZ^{(*)} \to 4\ell$ ,  $H \to \gamma \gamma$ , and  $H \to WW^{(*)} \to \ell \ell \gamma$  channels, including all systematic uncertainties. The markers indicate the maximum likelihood estimates  $(k, m_H)$  in the corresponding channels (the maximum likelihood estimates for  $H \to ZZ^{(*)} \to 4\ell$  and  $H \to WW^{(*)} \to \ell \ell \ell \gamma$  coincidence of the maximum likelihood estimates for  $H \to ZZ^{(*)} \to 4\ell$  and  $H \to WW^{(*)} \to \ell \ell \ell \gamma$  coincidence of the maximum likelihood estimates for  $H \to ZZ^{(*)} \to \ell \ell$  and  $H \to WW^{(*)} \to \ell \ell \ell \gamma$ .

Figure 17: The 68% CL contours for the signal strength  $\sigma/\sigma_{\rm SM}$  versus the boson mass  $m_{\rm X}$  for the untagged  $\gamma\gamma$ ,  $\gamma\gamma$  with VBF-like dijet,  $4\ell$ , and their combination. The symbol  $\sigma/\sigma_{\rm SM}$  denotes the production cross section times the relevant branching fractions, relative to the SM expectation. In this combination, the relative signal strengths for the three decay modes are constrained by the expectations for the SM Higgs boson.

I. Puljak: Data Analysis

CSC2019

.5 - 28 September 2019, Clui-Napoca

# Conclusions of papers - ATLAS

### 10. Conclusion

Searches for the Standard Model Higgs boson have been performed in the  $H{\to}ZZ^{(\circ)}{\to}4\ell$ ,  $H{\to}\gamma\gamma$  and  $H{\to}WW^{(\circ)}{\to}e\nu\mu\nu$  channels with the ATLAS experiment at the LHC using 5.8–5.9 fb<sup>-1</sup> of pp collision data recorded during April to June 2012 at a centre-of-mass energy of 8 TeV. These results are combined with earlier results [17], which are based on an integrated luminosity of  $4.6{-}4.8$  fb<sup>-1</sup> recorded in 2011 at a centre-of-mass energy of 7 TeV, except for the  $H{\to}ZZ^{(\circ)}{\to}4\ell$  and  $H{\to}\gamma\gamma$  channels, which have been updated with the improved analyses presented here.

The Standard Model Higgs boson is excluded at 95% CL in the mass range 111–559 GeV, except for the narrow region 122–131 GeV. In this region, an excess of events with significance  $59\sigma$ , corresponding to  $p_0=1.7\times10^{-9}$ , is observed. The excess is driven by the two channels with the highest mass resolution,  $H\to ZZ^{(0)}\to 4\ell$  and  $H\to\gamma\gamma$ , and the equally sensitive but low-resolution  $H\to WW^{(0)}\to tV\psi$  channel. Taking into account the entire mass range of the search, 110-600 GeV, the global significance of the excess is  $5.1\sigma$ , which corresponds to  $p_0=1.7\times10^{-3}$ .

These results provide conclusive evidence for the discovery of a new particle with mass  $126.0 \pm 0.4$  (stat)  $\pm 0.4$  (sys) GeV. The signal strength parameter  $\mu$  has the value  $1.4 \pm 0.3$  at the fitted mass, which is consistent with the SM Higgs boson hypothesis  $\mu = 1$ . The decays to pairs of vector bosons whose net electric charge is zero identify the new particle as a neutral boson. The observation in the diphoton channel disfavours the spin-1 hypothesis [140, 141]. Although these results are compatible with the hypothesis that the new particle is the Standard Model Higgs boson, more data are needed to assess its nature in detail.

I. Puljak: Data Analysis CSC2019 15 – 28 September 2019, Cluj-Napoca 24

# Conclusions of papers - CMS

Results are presented from searches for the standard model Higgs boson in proton-proton collisions at  $\sqrt{s}=7$  and 8 TeV in the CMS experiment at the LHC, using data samples corresponding to integrated luminosities of up to  $5.1\,{\rm fb}^{-1}$  at 7 TeV and  $5.3\,{\rm fb}^{-1}$  at 8 TeV. The search is performed in five decay modes:  $\gamma\gamma$ , ZZ, W+W-,  $\tau^+\tau^-$ , and b\overline{b}. An excess of events is observed above the expected background, with a local significance of  $5.0\,\sigma$ , at a mass near 125 GeV, signalling the production of a new particle. The expected local significance for a standard model Higgs boson of that mass is  $5.8\,\sigma$ . The global p-value in the search range of 115–130 (110–145) GeV corresponds to  $4.6\,\sigma$  ( $4.5\,\sigma$ ). The excess is most significant in the two decay modes with the best mass resolution,  $\gamma\gamma$  and ZZ, and a fit to these signals gives a mass of  $125.3\pm0.4$  (stat.)  $\pm0.5$  (syst.) GeV. The decay to two photons indicates that the new particle is a boson with spin different from one. The results presented here are consistent, within uncertainties, with expectations for a standard model Higgs boson. The collection of further data will enable a more rigorous test of this conclusion and an investigation of whether the properties of the new particle imply physics beyond the standard model.

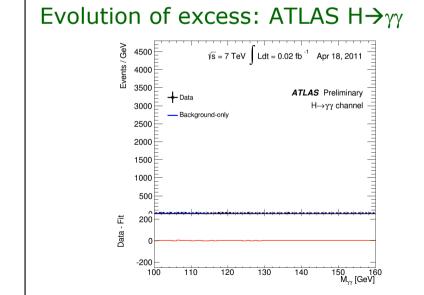
We'll come back to this at the end of lectures

I Puliak: Data Analysi

CSC2019

15 - 28 September 2019, Clui-Napo

### Evolution of excess: CMS $H \rightarrow 77 \rightarrow 41$ **CMS** Preliminary GeV Data $\sqrt{s}$ = 7 TeV: L = 0.0 fb<sup>-1</sup> \_\_\_ m<sub>н</sub>=126 GeV က $Z\gamma^*,ZZ$ Events / Z+X 10F 800 80 100 200 300 400 600 m<sub>41</sub> [GeV]



# Evolution of language

- February 2012
  - Combined results of searches for the standard model Higgs boson in pp collisions at sqrt(s) = 7 TeV
  - By CMS Collaboration, Phys. Lett. B710 (2012) 26-48
- July 2012
  - Observation of a new boson with a mass of 125 GeV with the CMS experiment at the LHC
  - By CMS Collaboration, Phys. Lett. B716 (2012) 30-61
- December 2012
  - Study of the Mass and Spin-Parity of the Higgs Boson Candidate Via Its Decays to Z Boson Pairs
  - By CMS Collaboration, Phys. Rev. Lett. 110 (2013) 081803
- July 2013
  - Measurements of Higgs boson production and couplings in diboson final states with the ATLAS detector at the LHC
  - By ATLAS Collaboration, Phys. Lett. B 726 (2013) 88
- March 2015
  - Combined Measurement of the Higgs Boson Mass in pp Collisions at sqrt(s)
     7 and 8 TeV with the ATLAS and CMS Experiments
  - By ATLAS and CMS Collaborations, Phys.Rev.Lett. 114 (2015) 191803

Puljak: Data Analysis CSC2019 15 - 28 September 2019, Cluj-N

### **Outline of Lecture Series**

- Introduction, Monte Carlo methods and distributions
- 2. Estimators and confidence intervals
- 3. Confidence intervals
- 4. Hypothesis testing

[. Puljak: Data Analysis

CSC2019

15 - 28 September 2019, Clui-Napoca

# **Data Analysis**

Lecture 1: Introduction to data analysis and Monte Carlo methods

I. Puljak: Data Analysis

CSC2019

15 - 28 September 2019, Clui-Napoc

### In this lecture

- Introduction to data analysis
  - Confirmatory and exploratory data analysis
  - Quantitative vs graphical techniques
  - Experimental vs observational studies
  - Exploring the data

# Data analysis, statistics and probability

 Data analysis is the process of transforming raw data into usable information

RAW data

Data analysis

Usable information

- Data analysis uses statistics for presentation and interpretation (explanation) of data
  - Descriptive statistics
    - Describes the main features of a collection of data in quantitative terms
  - Inductive statistics
    - Makes inference about a random process from its observed behavior during a finite period of time
- A mathematical foundation for statistics is the probability theory

er 2019, Cluj-Napoca 31

.5 - 28 September 2019, Cluj-Napoca

### Confirmatory and exploratory data analysis

- Confirmatory data analysis = Statistical hypothesis testing
  - A method of making statistical decisions using experimental data
  - Two main methods
    - Frequentist hypothesis testing
      - Hypothesis is either true or not
    - Bayesian inference
      - Introduces a "degree of belief"
- Exploratory data analysis
  - Uses data to suggest hypothesis to test
  - Complements confirmatory data analysis
  - Main objectives:
    - Suggest hypothesis about the causes of observed phenomena
    - Asses assumptions on which statistical inference will be based
    - Select appropriate statistical tools and techniques
    - Eventually suggest further data collection

I. Puljak: Data Analysis

CSC2019

15 - 28 September 2019, Clui-Napoca

# Quantitative vs graphical techniques

- Quantitative techniques yield numeric or tabular output
  - Hypothesis testing
  - Analysis of variance
  - Point estimation
  - Interval estimation

### Graphical techniques

- Used for gaining insight into data sets in terms of testing assumptions, model selection, estimator selection ...
- Provide a convincing mean of presenting results
- Includes: graphs, histograms, scatter plots, probability plots, residual plots, box plots, block plots, biplots
- Four main objectives:
  - Exploring the content of a data set
  - Finding structure in data
  - Checking assumptions in statistical models
  - Communicate the results of an analysis

I. Puljak: Data Analysis

CSC2019

15 – 28 September 2019, Clui-Napoca

# Experimental vs observational studies

Experimental studies



 Example: Study of whether and how much a free coffee would improve working performace of scientists in Building 40 at CERN

### Observational studies

- No experimental manipulation
- Data are gathered and analysed
- Example:
  - Study of correlation between number of beers drunk in a pub on Wednesday evening on performance on the exam the day after
  - Be careful who pays! → see later
  - One could discuss whether to manipulate or not the system ©

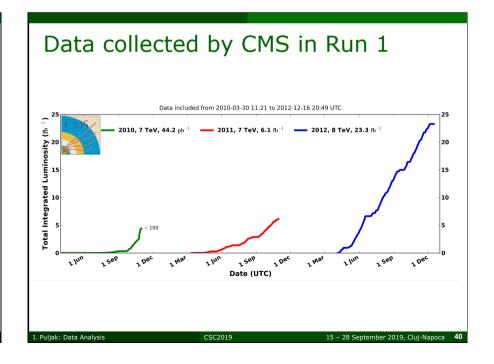
Experiments – basic steps · Select subject to study **Planning** · Select an information source · Design an experiment Design and • Build and test a model (f.g. MC simulation) Building Once happy with the model build the experiment • Employ descriptive statistics to summarize data Collecting data Suppres details Early exploratory analysis Statistical inference **Analysing data** · Reach a consensus what observations tell about an underlaying reality Presenting Publish article and disseminate results Documenting • Enjoy in the fruits of the hard work! I. Puljak: Data Analysis 15 - 28 September 2019, Cluj-Napoca

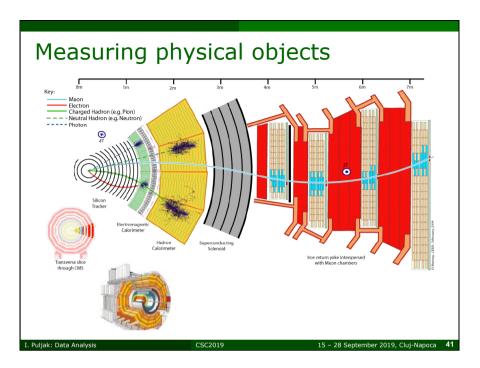
I. Puljak: Data Analysis CSC2019 15 – 28 September 2019, Cluj-Napoca

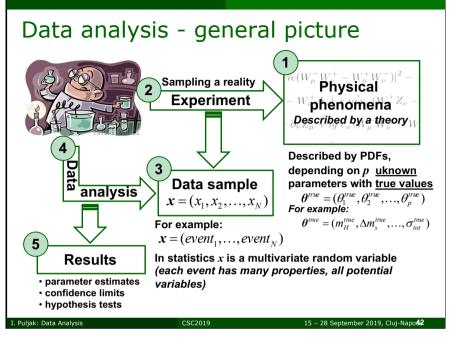
### LHC experiments – basic steps Started ~ 30 years ago (Aachen 1989) Planning Core teams from previous experiments UA1&2 · 'Best' experimental design chosen (CMS. Design ATLAS, ALICE and LHCb) Building Detailed MC simulations performed before started to build Trigger and DAQ carefully planed and built Collecting data • MC simulation used for optimization Statistical inference → a part of work done **Analysing data** at this school too (learning methods&tools) For the consensus → let's see © Presenting · Many articles published **Documenting** And first discoveries announced and published! I. Puljak: Data Analysis 15 - 28 September 2019, Cluj-Napoca

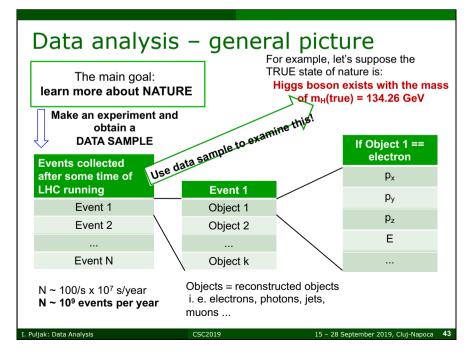
### What we (will) measure at LHC? Something we already know Something that (probably) exists but wasn't measured vet • At the very beggining of the LHC operation • For example: production of W and Z Simply because we are exploring new bosons energy domain Standard Model processes But surprises are always possible Hopefully something new but Maybe something new but less reasonably expected likely • Altought "reasonably" is not very well • New heavy bosons (Z', W') defined © Micro black holes • For example we all expected to find the Extra dimensions Higgs boson → and we did find it! Heavy neutrions? Something completely unexpected • Well, it's hard to look for unexpected @

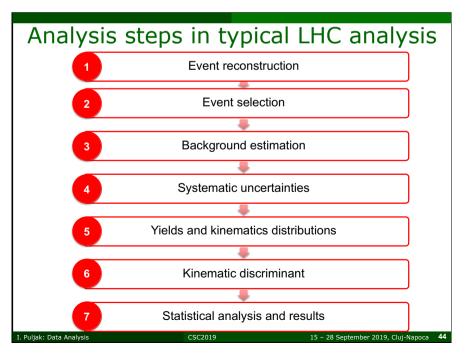
# Some of the physicists' jargon Cross section (σ) A measure of 'frequency' of the physical process Units: barns (10-28 cm²) Typical values: femtobarns (fb), picobarns (pb) Luminosity (L) Or instantenous luminosity A measure of collisions 'frequency' Typical (at Tevatron/Early LHC): L = 10<sup>32</sup> cm<sup>-2</sup>s<sup>-1</sup> Integrated luminosity (∠ = ∫Ldt) A measure of number of accumulated collisions after a certain time period Units: (cross section)<sup>-1</sup> .... E.g. 1 fb<sup>-1</sup> = 1000 pb<sup>-1</sup> Typical (Tevatron/Early LHC): few fb<sup>-1</sup> Number of events (N)





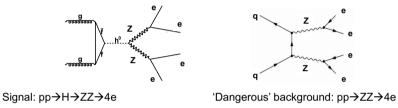








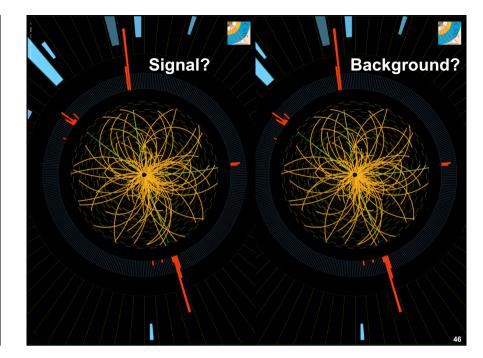
- Signal: an event coming from the physical process under study
  - Example:  $H \rightarrow ZZ \rightarrow e^+e^-e^+e^-$  (henceforth both  $e^+$  and  $e^-$  are 'electron')
- Background: any other event
  - 'Dangerous' background is any other process giving at least 4 electrons in the final state
    - But be careful: electrons seen by detector are reconstructed objects and in some cases when some other objects (f.g. jets) are misreconstructed as electrons
  - `Trivial' backgrounds are all other backgrounds and are easily rejected by a simple requirement of having at least 4 electrons in the final state



i. Puljak: Data Analysis

CSC2019

15 - 28 September 2019, Cluj-Napoca



# Separating signal and background

- Ultimate goal of the analysis: separate as much as possible signal from background events to obtain a reduced sample as clean as possible
  - This is usually obtained in several steps



- Usually all these steps have substeps
- More in example on the next page
- Be aware:
  - Nature is probabilistic, i.e. for a given event it'll never be possible to tell whether it's signal or background!
  - We can only make an educated guess → attribute probabilities that the observed event comes from signal or background

### p(event|signal) and p(event|background)

 Very often we have to solve the following statistical problem: maximum reduction of the background for a given signal acceptance

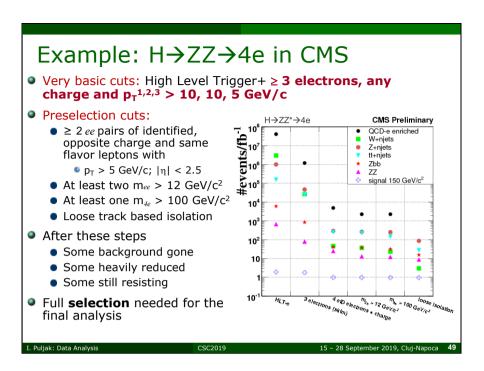
# Exploring the data

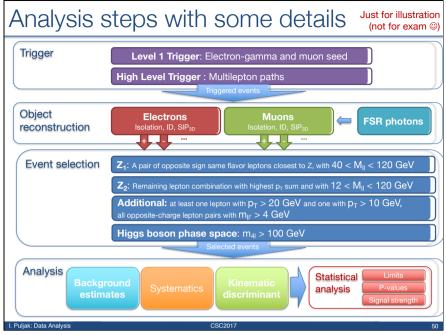
- Once data are collected → exploratory data analysis
  - Heavily use of graphical techniques
- Example: data reduction = Preselection
  - Goal: getting rid of all unuseful events
  - Unusefullness is not uniquely defined:
    - We have a certain interest to keep some background events for better control and its measurement from data
  - Some numbers:
    - ~ 109 events collected per year (after trigger)
    - ~ 1 MB event size on a tape (rought estimate)
    - $\bullet \Rightarrow \sim 1$  PB of data collected per year  $\rightarrow$  non manageable at once
  - Interested physical processes are rare

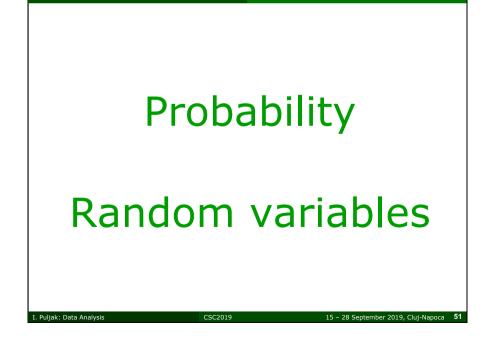
    - So be careful when choosing criteria for data reduction not to lose too many signal events

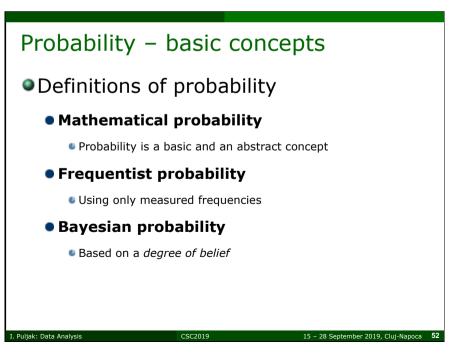
I. Puljak: Data Analysis

15 - 28 September 2019, Cluj-Napoca









# Mathematical probability

- Developed in 1933 by Kolmogovor in his "Foundations of the Theory of Probability"
- $\circ$  Define  $\Omega$  as an exclusive set of all possible elementary events  $x_i$ 
  - Exclusive means the occurrence of one of them implies that none of the others occurs
- We define the probability of the occurrency of  $x_i$ ,  $P(x_i)$  to obey the Kolmogorov axioms:

(a) 
$$P(x_i) \ge 0$$
 for all i

(b) 
$$P(x_i \text{ or } x_i) = P(x_i) + P(x_i)$$

$$(c)\sum_{\Omega}P(x_i)=1$$

- From these properties more complex probability expressions can be deduced
  - For non-elementary events, i.e. set of elementary events
  - For non-exclusive events, i.e. overlapping sets of elementary events

I. Puljak: Data Analysis

# Bayesian probability

- Based on a concept of "degree of belief"
- An operational definition of belief is based on coherent bet by Finneti
  - What's amount of money one 's willing to bet based on her/his belief on the future occurence of the event
- Bavesian inference uses Baves' formula for conditional probability:

$$P(H \mid D) = \frac{P(D \mid H)P(H)}{P(D)}$$

- H is a **hypothesis**, and D is the **data**.
- P(H) is the **prior probability** of H: the probability that H is correct before the data D was seen.
- P(D|H) is the **conditional probability** of seeing the data D given that the hypothesis H is true. P(D|H) is called the **likelihood**.
- $\bullet$  P(D) is the **marginal probability** of D.
  - $\bullet$  P(D) is the prior probability of witnessing the data D under all possible hypotheses
- P(H|D) is the **posterior probability**: the probability that the hypothesis is true, given the data and the previous state of belief about the hypoth.

# Frequentist probability

- Experiment:
  - N events observed
  - Out of them n is of type x
- Frequentist probability that any single event will be of type x

$$P(x) = \lim_{N \to \infty} \frac{n}{N}$$

- Important restriction: such a probability can only be applied to repeatable experiments
  - For example one can't define a probability that it'll snow tomorrow
  - Altough this seems to be a serious problem, a job of scientist is to try to get as close as possible to repeatable experiments and produce reproducible results
- Frequentist statistics is often associated with the names of Jerzy Nevman and Egon Pearson

A. Heikinnen, CSC 2009, Göttingen

### Example: Who will pay the next round?

You meet an old fried at Göttingen in a pub. He proposes that the next round should be payed by whichever of the two extracts the card of lower value from a pack of cards.

This situation happens many times in the following days. What is the probability that your friend cheats if you end up paying wins consecutive times<sup>2</sup> You assume:

- P(cheat) = 5% and P(honest) = 95%. (Surely an old friend is an unlikely cheater ...)
- P(wins|cheat) = 1 and  $P(wins|honest) = 2^{-wins}$

Bavesian solution:

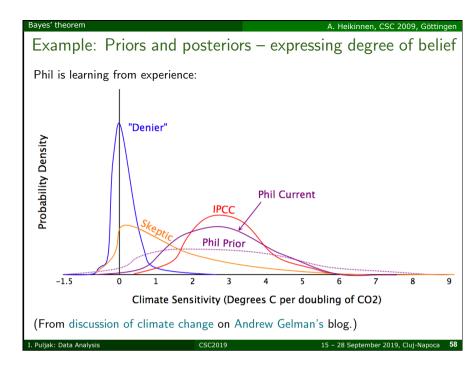
$$P(cheat|wins) = \frac{P(wins|cheat)P(cheat)}{P(wins|cheat)P(cheat) + P(wins|honest)P(honest)}$$

$$1P(cheat) = \frac{P(wins|cheat)P(cheat)}{P(wins|honest)P(honest)}$$

$$\begin{split} P(\textit{cheat}|0) &= \frac{1P(\textit{cheat})}{1P(\textit{cheat}) + 2^{-0}P(\textit{honest})} = \frac{0.05}{0.05 + 0.95} = 5\% \\ P(\textit{cheat}|5) &= \frac{1P(\textit{cheat})}{1P(\textit{cheat}) + 2^{-5}P(\textit{honest})} = \frac{0.05}{0.05 + 0.03} = 63\% \end{split}$$

<sup>&</sup>lt;sup>2</sup>Adapted from G. D'Agostini, Bayesian Reasoning in High-Energy Physics: Principles and Applications, CERN-99-03, 1999

Bayesian statistics: Learning from experience A. Heikinnen, CSC 2009, Göttingen Example: Learning by experience The process of updating the probability when new experimental data becomes available can be followed easily if we insert • P(cheat) = P(cheat|wins - 1) and P(honest) = P(honest|wins - 1). where wins - 1 indicate the propability assigned after the previous win • P(wins = 1|cheat) = P(win|cheat) = 1 and  $P(wins = 1|honest) = P(win|honest) = \frac{1}{2}$ Iterative aplication of the Bayes formula for P(cheat|wins)= P(win|cheat)P(cheat|wins - 1)P(win|cheat)P(cheat|wins - 1) + P(win|honest)P(honest|wins - 1)P(cheat|wins - 1) $= \frac{1}{P(cheat|wins-1) + \frac{1}{2}P(honest|wins-1)}$ P(cheat wins) P(cheat) When you learn from the wins=5 10 experience, vour conclu-99.7 1 24 91 sions no longer depend on 5 63 99.94 the initial assumptions. 50 97 99.9 99.997



# Random variables

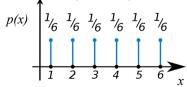
- Random event: event having more than one possible outcome
  - Each outcome may have associated probability
  - Outcome not predictible, only the probabilities known
- Different possible outcomes may take different possible numerical values  $x_1, x_2, ... \rightarrow$  random variable x
  - The corresponding probabilities  $P(x_1)$ ,  $P(x_2)$ , ... form a **probability distribution**
- If observations are independent the distribution of each random variable is unaffected by knowledge of any other observation
- When an experiment consists of N repeated observations of the same random variable x, this can be considered as the single observation of a random vector x, with components  $x_1, ..., x_N$



- Rolling a die:
  - Sample space =  $\{1,2,3,4,5,6\}$
  - Random variable x is the number rolled

$$x = \begin{cases} 1 & \text{if a 1 is rolled} \\ 2 & \text{if a 2 is rolled} \\ 3 & \text{if a 3 is rolled} \\ 4 & \text{if a 4 is rolled} \\ 5 & \text{if a 5 is rolled} \\ 6 & \text{if a 6 is rolled} \end{cases}$$

• Discrete probability distribution





I. Puljak: Data Analysis

15 - 28 September 2019, Cluj-Napo

# Random variables: continuous

- A spinner
  - Can choose a real number from [0,2n]
  - All values equally likely
  - $\bullet$  X = the number spun
  - Probability to select any real number = 0
  - Probability to select any range of values > 0
    - Probability to choose a number in [0,n] = 1/2
  - Now we say that probability **density** p(x) of x is 1/2n
  - Probability to select a number from any range  $\Delta x$  is  $\Delta x/2n$
  - More general

$$P(A < x < B) = \int_{A}^{B} p(x) dx$$

# Probability density function

- Let x be a possible outcome of an observation and can take any value from a continuous range
- We write  $f(x; \theta)dx$  as the probability that the masurement's outcome lies betwen x and x + dx
- The function  $f(x;\theta)dx$  is called the **probability density function** (PDF)
  - And may depend on one or more parameters  $\theta$
- If  $f(x; \theta)$  can take only **discrete values** then  $f(x; \theta)$  is itself a probability
- The p.d.f. is always normalized to unit area (unit sum, if discrete)
- Both x and  $\theta$  may have multiple components and then written as vectors
- If  $\theta$  is unknown we may wish to estimate its value from a set of measurements of  $x \rightarrow$  Parameter estimation in Lecture 3

# Cumulative and marginal distributions

### Cumulative distribution function, CDF

• For every real number Y, the CDF of Y is equal to the probability that the random variable x takes a value less or equal to Y

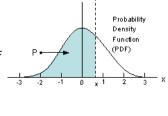
$$F(Y) = P(x \le Y) = \int_{Y}^{Y} f(x) dx$$

- If x restricted to  $x_{min} < x < x_{min}$  then  $F(x_{min})$  $= 0, F(x_{max}) = 1$
- $\bullet$  F(x) is a monotonic function of x

### Marginal density function

- Is the projection of multidimensional density
- Example: if f(x,y) is two-dimensional PDF the marginal density g(x) is

$$g(x) = \int_{y_{\text{max}}}^{y_{\text{max}}} f(x, y) dy$$

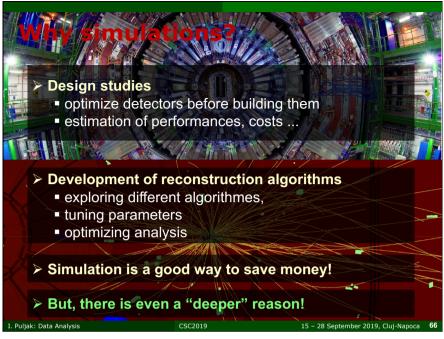


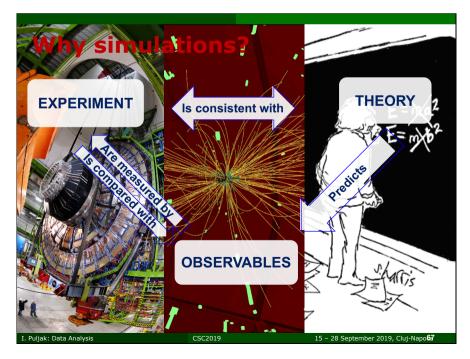
Distribution Function

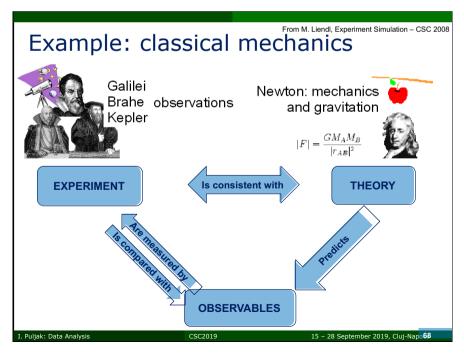
Introduction to Monte Carlo method

- Monte Carlo techniques
- Monte Carlo in HEP









This and many follwing pages adopted from Wikipedia

# Monte Carlo method

- Monte Carlo methods (MCMs) are a class of computational algorithms that rely on repeated random sampling to compute their results
  - MCMs use random or pseudo-random numbers
  - MCMs tend to be used when it is unfeasible or impossible to compute an exact result with a deterministic algorithm
- The term "Monte Carlo method" was coined in the 1940s by physicists working on nuclear weapon projects in the Los Alamos National Laboratory
- Generally MCMs are used in
  - Studying systems with a large number of coupled (interacting) degrees of freedom
    - such as fluids, disordered materials, strongly coupled solids, and cellular structures
  - Modeling phenomena with significant uncertainty in inputs
    - such as the calculation of risk in business
  - Evaluation of definite integrals
    - particularly multidimensional integrals with complicated boundary conditions

I Puliak: Data Analysis

CSC201

15 - 28 September 2019, Cluj-Napoca

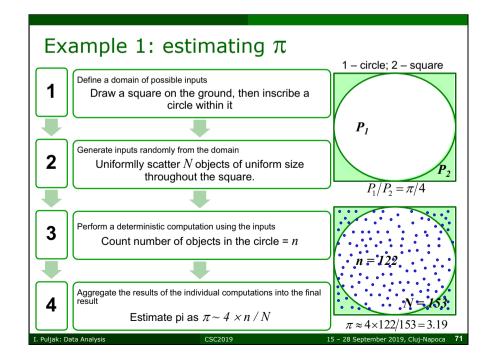
Monte Carlo Methods – usual pattern

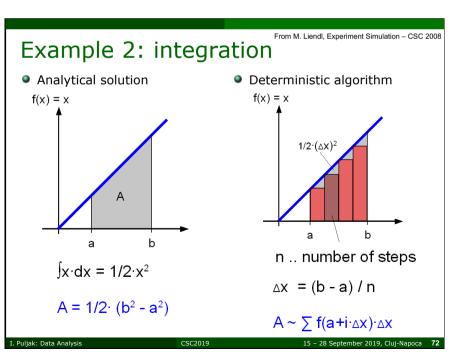
1 Define a domain of possible inputs

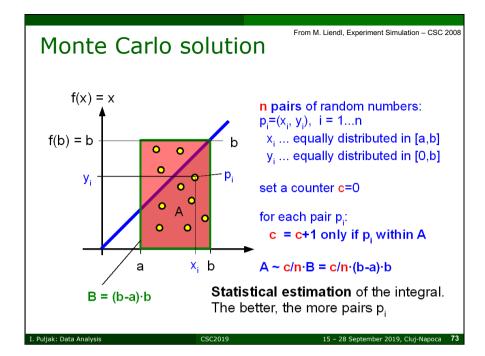
2 Generate inputs randomly from the domain

3 Perform a deterministic computation using the inputs

4 Aggregate the results of the individual computations into the final result







# Random number generation

### Physical methods

- "true" random numbers from "unpredictable" process
  - Example: dice, coin flopping, roulette → still in use
- TRUE random numbers from random atomic or subatomic physical phenomena
  - Example: radioactive decay, amplitude of noise in radio

### Computational methods

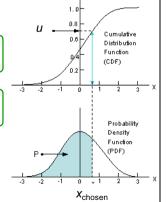
- Pseudo-random number generators create long runs (for example, millions of numbers long) with good random properties but eventually the sequence repeats
  - Example: Linear congruential generator  $X_{n+1} = (aX_n + b) \mod m$

### • Generation from a probability distribution f(x)

- Generate random numbers distributed according to the f(x)
- Method involves transforming an uniform random number in some
  - Examples: inversion method, acceptance-rejection method

# Inversion method

- Let x be a random variable whose distribution can be described by the cumulative distribution function F(x).
- We want to generate values of x which are distributed according to this distribution.
- Method:
  - 1. Generate a random number from the standard uniform distribution: call this u.
- 2. Compute the value x such that F(x) = u; call this  $x_{chosen}$
- 3. Take  $x_{\text{chosen}}$  to be the random number drawn from the distribution described by *F*.



# Acceptance-rejection method

- It generates sampling values from an arbitrary PDF function f(x) by using an instrumental distribution h(x) for which we know how to
  - under the only restriction that f(x) < Ch(x) where C > 1
- Usualy used in cases where the form of f(x) makes sampling difficult
- Algorithm

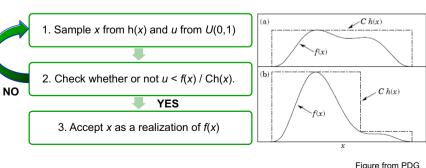


Figure from PDG

15 - 28 September 2019, Cluj-Napoca 76

I. Puljak: Data Analysis

15 - 28 September 2019, Cluj-Napoca

# MC methods in engineering

### Wireless network planing

- Various scenaria depending on: number of users, users' location, services users want to use
- MC used to generate users and their states, so that network performace can be evaluated and optimized

### Computer graphics

- MC methods efficient in production of photorealistic images of virtual 3D models
- Application in video games, computer generated films, special effects in cinema

### Wind power engineering

 From measured distributions of wind speeds MC generates single values for wind power sistem performace evaluation and optimization

I. Puliak: Data Analysis

CSC2019

15 – 28 September 2019, Cluj-Napoca

### Adopted from T. Siöstrand, CERN Academic Training Lectures 2005 Monte Carlo in HEP 'Real life' **Simulation Event Generation Collisions** Tools: MC generators (PYTHIA, ...) Tools: Accelerator (LHC, Tevatron ...) Output: final state particles Output: final state particles **Detector simulation** Data acquisition Tools: MC simulators (GEANT) Tools: Detectors (CMS. ATLAS....) Output: simulated detector response Output: detector response **Event reconstruction** Tools: Detectors' software packages (custom made; MC used in algorithms) Output: reconstructed physical objects (electrons, muons, jets ...) **Data analysis** Tools: Statistics (ROOT. ...: MC used in algorithms: f.g. Tov MC) Output: new knowledge (parameter/interval estimates, hypothesis tests, article, talks ...) I. Puljak: Data Analysis 15 - 28 September 2019, Cluj-Napoca

# Monte Carlo in HEP

- Monte Carlo methods are widely used in High Energy Physics
  - Theoretical calculations
    - Total cross sections, differential cross sections distributions ...

### Event generation

- Distribute events according to expected probabilites
- Many event generators on the market: f.g. PYTHIA, HERWIG

### Detector simulation

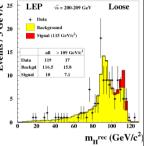
- Passage of particles through the matter
- GEANT

### Data analysis

- Background predictions (if not measured from data)
- Signal predictions
- Final results

CSC2019

THE SAMPRICAL LOSS



15 = 28 Sentember 2019, Clui-Nanoca