CMS Statistical analysis tool COMBINE

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- 1. Розподіли ймовірності
- 2. Статистичне тестування гіпотез
- 3. CMS combine

Література

Викладки та ілюстрації базується на матеріалах з

- Luca Lista. Statistical Methods for Data Analysis With Applications in Particle Physics. (Lecture Notes in Physics)
- Препринт. The CMS Collaboration. The CMS statistical analysis and combination tool: COMBINE (arxiv.org)
- CMS Higgs boson observation statistical model (repository.cern)

Installing

- Docker or podman
 - Docker Desktop: The #1 Containerization Tool for Developers | Docker
 - o podman/docs/tutorials/podman-for-windows.md at main · containers/podman (github.com)
 - Requires WSL2 on Windows
 - Requires xqartz and socat packages in MacOS (see next slide)



docker run -it --rm -e DISPLAY=\$DISPLAY -v /tmp/.X11-unix:/tmp/.X11-unix gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1

or



podman run -it gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1

Installing on MacOS

Follow instructions at Running GUI's with Docker on Mac OS X | by Nils De Moor | Containerizers (cntnr.io)

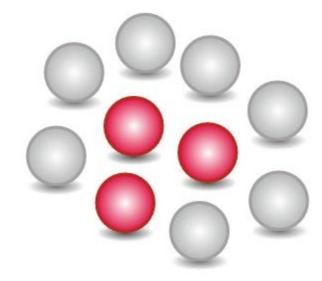
```
> brew install socat
> socat TCP-LISTEN:6000,reuseaddr,fork UNIX-CLIENT:\"$DISPLAY\"
> brew install xquartz
> open -a Xquartz
> ifconfig en0
    en0:
    ...
inet 192.168.0.235 netmask 0xffffff00 broadcast 192.168.199.255
```

- Use IP address of the server in your *docker run* commands, e.g.
- docker run -it --rm -e DISPLAY=192.168.0.235:0 -v /tmp/.X11-unix:/tmp/.X11-unix gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1

Bernoulli distribution

$$\begin{cases} P(1) = p, \\ P(0) = 1 - p. \end{cases}$$
 (2.55)

Fig. 2.1 A set of R = 3 red balls plus W = 7 white balls considered in a Bernoulli process. The probability to randomly extract a red ball is $p = R/(R + W) = \frac{3}{10} = 30\%$



Binomial distribution

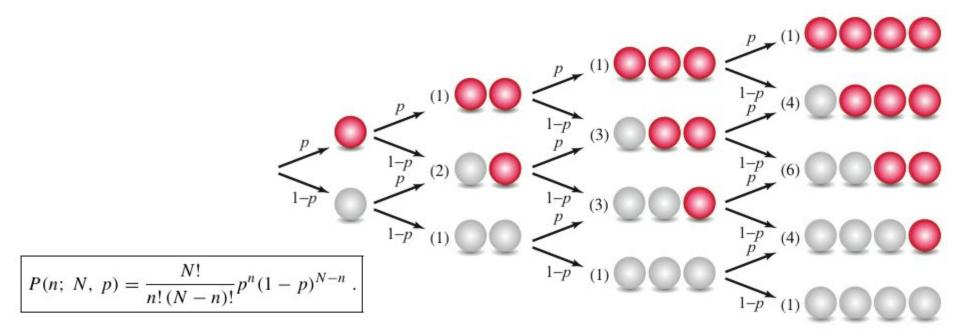


Fig. 2.2 Binomial process represented as subsequent random extractions of a single red or white ball (Bernoulli process). The tree shows all the possible combinations at each extraction step. Each branching has a corresponding probability equal to p or 1 - p for a red or white ball, respectively. The number of paths corresponding to each possible combination is shown in parentheses and is equal to the binomial coefficient in Eq. (2.60)

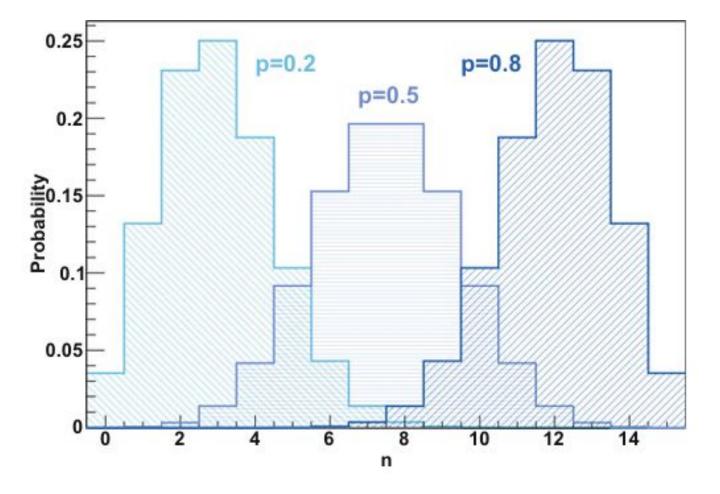


Fig. 2.4 Binomial distributions for N=15 and for $p=0.2,\,0.5$ and 0.8

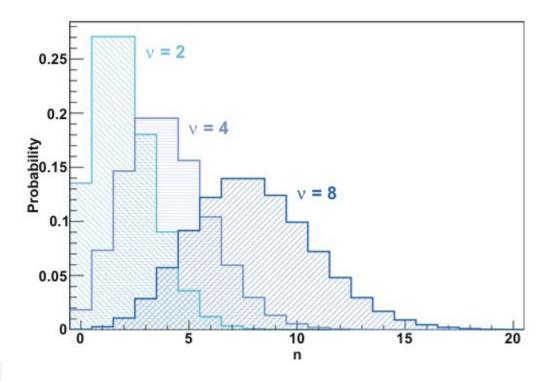
Poisson distribution is a limit of binomial distribution

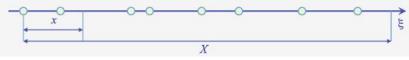
$$p -> 0$$

$$P(n; \ v) = \frac{v^n e^{-v}}{n!} \ .$$

$$Np \rightarrow v$$

Poisson distribution is also obtained from sampling n uniformly distributed points from [0;x) in the limit $N \rightarrow \infty$ $X \rightarrow \infty$, but fixed density N/X = r, v = < n > = Nx/X = rx





Poisson distributions with different value of the rate parameter ν

Large *v* limit converges to Gaussian distribution

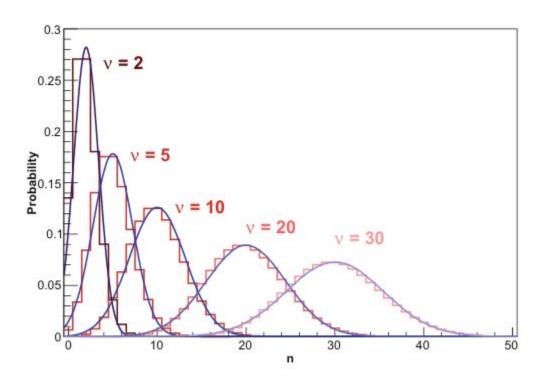


Fig. 2.6 Poisson distributions with different value of the parameter ν compared with Gaussian distributions with $\mu = \nu$ and $\sigma = \sqrt{\nu}$

X² distribution

Sum of independent normally distributed random variables

$$\chi^2 = \sum_{j=1}^k z_i^2 \ .$$

$$\chi^2 = \sum_{j=1}^k \frac{(x_j - \mu_j)^2}{\sigma_j^2}$$
.

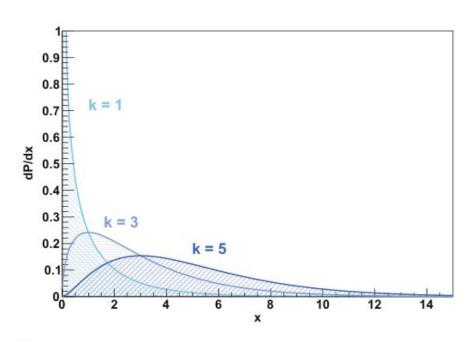


Fig. 3.3 χ^2 distributions with different numbers of degrees of freedom k

Likelihood function

The joint probability density function of the random variables x₁, x₂, ... x_n

$$L(x_1, \dots, x_n; \theta_1, \dots, \theta_m) = \frac{\mathrm{d}P(x_1, \dots, x_n; \theta_1, \dots, \theta_m)}{\mathrm{d}x_1 \dots \mathrm{d}x_n}.$$

 In case of independent observations, likelihood is a product of individual PDFs for each observation

$$L(\vec{x}_1, \cdots, \vec{x}_N; \vec{\theta}) = \prod_{i=1}^N p(\vec{x}_i; \vec{\theta}).$$

• It is more convenient to work with sums rather than products, therefore

$$-\log L(\vec{x}_1, \dots, \vec{x}_N; \vec{\theta}) = -\sum_{i=1}^{N} \log p(\vec{x}_i; \vec{\theta}).$$

Neyman Confidence Intervals

Two steps:

- 1. Construction of a confidence belt
- 2. Inversion of the confidence belt

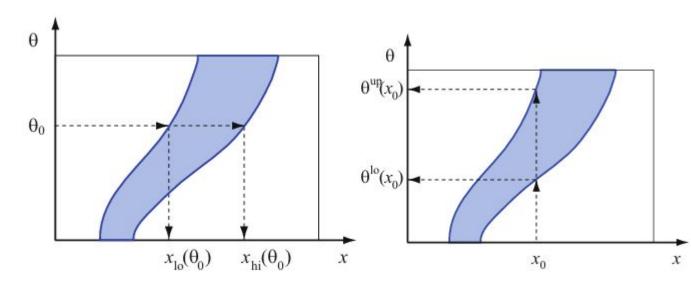


Fig. 8.1 Illustration of Neyman belt construction (left) and inversion (right)

$$1 - \alpha = \int_{x^{\log(\theta_0)}}^{x^{\sup(\theta_0)}} f(x \mid \theta_0) \, \mathrm{d}x .$$

Neyman Confidence Intervals contd.

Two steps:

- Construction
 of a confidence
 belt
- Inversion of the confidence belt

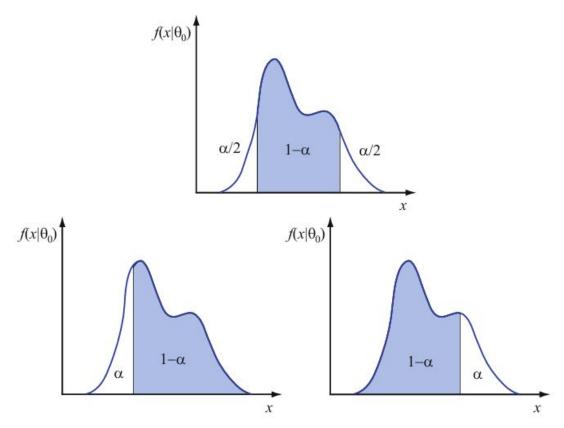


Fig. 8.2 Three possible choices of ordering rule: central interval (top) and fully asymmetric intervals (bottom left, right)

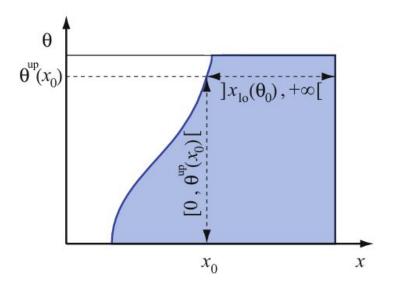


Fig. 12.3 Illustration of Neyman belt construction for upper limits determination

$$P(n; s) = \frac{e^{-s}s^n}{n!}$$
. $p = P(0; s) = e^{-s}$, $p = e^{-s} > \alpha$ $s < -\log \alpha = s^{\text{up}}$. $s < 3.00$ at 95% CL, $s < 2.30$ at 90% CL.

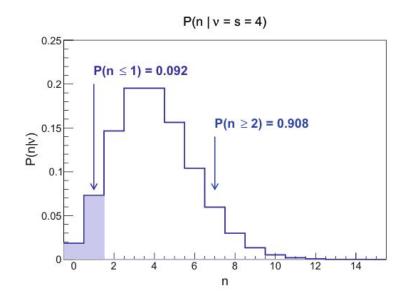
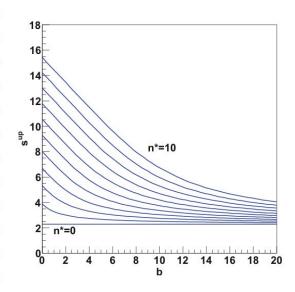


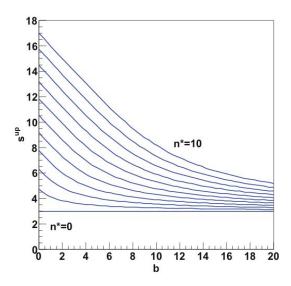
Fig. 12.4 Poisson distribution of the total number of counts n = s + b for s = 4 and b = 0. The white bins show the smallest possible fully asymmetric confidence interval, $\{2, 3, 4, \dots\}$ in this case, that gives at least the required coverage of 90%

$$\alpha = e^{-s^{up}} \frac{\sum_{m=0}^{n^{\star}} (s^{up} + b)^m / m!}{\sum_{m=0}^{n^{\star}} b^m / m!},$$

Upper limits in the presence of negligible background

n*	$1 - \alpha = 90\%$	$1 - \alpha = 95\%$
	s ^{up}	sup
0	2.30	3.00
1	3.89	4.74
2	5.32	6.30
3	6.68	7.75
4	7.99	9.15
5	9.27	10.51
6	10.53	11.84
7	11.77	13.15
8	12.99	14.43
9	14.21	15.71
10	15.41	19.96





Hypothesis testing

According to Neyman-Pearson lemma, the likelihood ratio

$$\lambda(\vec{x}\,) = \frac{L(\vec{x} \mid H_1)}{L(\vec{x} \mid H_0)} \,.$$

Achieves
Largest signal
selection efficiency

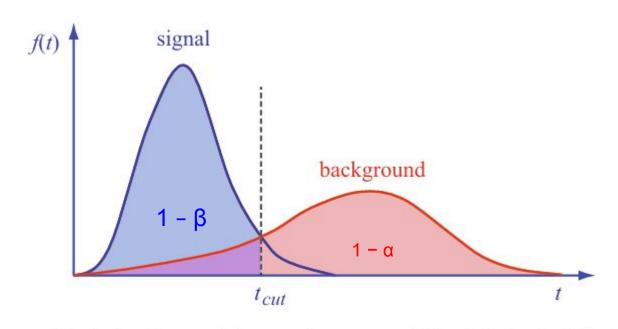
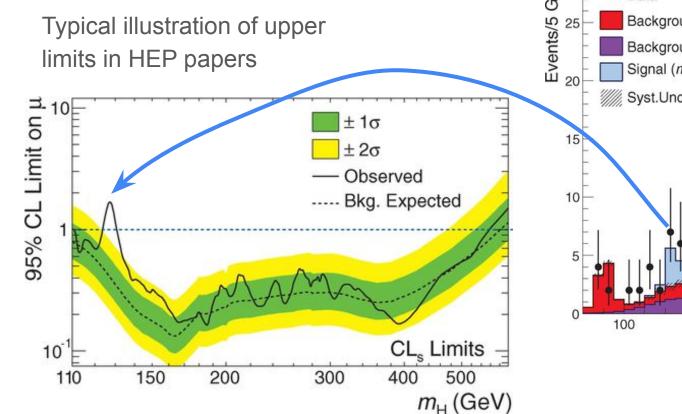
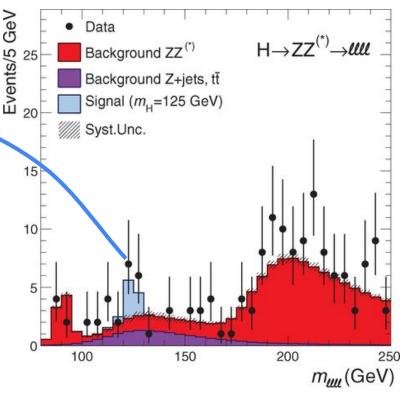


Fig. 10.1 Distribution of a test statistic *t* according to two possible PDFs for the signal (blue) and background (red) hypotheses under test

1 - β for fixed background misidentification probability α

Brazilian plot

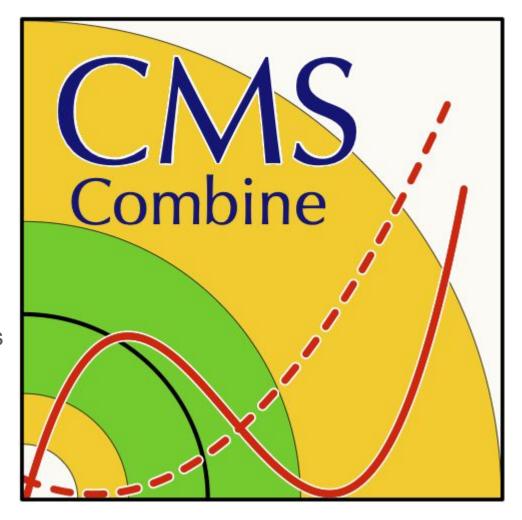




Combine tool

Combine (cms-analysis.github.io)

The package, originally designed to perform searches for a Higgs boson and the combined analysis of those searches, has evolved to become the statistical analysis tool presently used in the majority of measurements and searches performed by the CMS Collaboration



Counting experiment

- docker run [--platform linux/amd64] -it
 gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1
- combine data/tutorials/CAT23001/datacard-1-counting-experiment.txt
 - LHC-style: --LHCmode LHC-limits. The test statistic is defined using a ratio of profile likelihoods,

$$\widetilde{q}_{LHC}(\mu) = \begin{cases}
-2 \ln \left(\frac{\mathcal{L}(\mu, \hat{\vec{v}}(\mu))}{\mathcal{L}(\hat{\mu}, \hat{\vec{v}})} \right) & \text{if } 0 \leq \hat{\mu} \leq \mu, \\
-2 \ln \left(\frac{\mathcal{L}(\mu, \hat{\vec{v}}(\mu))}{\mathcal{L}(0, \hat{\vec{v}}(0))} \right) & \text{if } \hat{\mu} < 0, \\
0 & \text{if } \hat{\mu} > \mu,
\end{cases} \tag{24}$$

Wilk's theorem

• Wilk's theorem ensures that in the limit of the test statistic follows χ^2 distribution with 1 degree of freedom

$$\chi_r^2 = -2\log \frac{\sup_{\vec{\theta} \in \Theta_0} \prod_{i=1}^N L(\vec{x}_i \; ; \; \vec{\theta} \;)}{\sup_{\vec{\theta} \in \Theta_1} \prod_{i=1}^N L(\vec{x}_i \; ; \; \vec{\theta} \;)}.$$

This property is applied in combine AsymptoticLimit option

Applying Wilk's theorem to searches test statistic

$$L(\vec{x}_{1}, \dots, \vec{x}_{N}; \vec{\theta}) = \frac{e^{-\nu(\vec{\theta})}\nu(\vec{\theta})^{N}}{N!} \prod_{i=1}^{N} f(\vec{x}_{i}; \vec{\theta}),$$

$$f(\vec{x}; \vec{\theta}) = \frac{\mu s}{\mu s + b} f_{s}(\vec{x}; \vec{\theta}) + \frac{b}{\mu s + b} f_{b}(\vec{x}; \vec{\theta}).$$

$$L_{s+b}(\vec{x}_{1}, \dots, \vec{x}_{N}; \mu, \vec{\theta}) = \frac{e^{-(\mu s(\vec{\theta}) + b(\vec{\theta}))}}{N!} \prod_{i=1}^{N} (\mu s f_{s}(\vec{x}_{i}; \vec{\theta}) + b f_{b}(\vec{x}_{i}; \vec{\theta})).$$

$$L_{b}(\vec{x}_{1}, \dots, \vec{x}_{N}; \vec{\theta}) = \frac{e^{-b(\vec{\theta})}}{N!} \prod_{i=1}^{N} b f_{b}(\vec{x}_{i}; \vec{\theta}).$$
(10.33)

Applying Wilk's theorem to searches test statistic

$$\lambda(\mu, \vec{\theta}) = \frac{L_{s+b}(\vec{x}_1, \dots, \vec{x}_N; \mu, \vec{\theta})}{L_b(\vec{x}_1, \dots, \vec{x}_N; \vec{\theta})} =$$

$$= \frac{e^{-(\mu s(\vec{\theta}) + b(\vec{\theta}))}}{e^{-b(\vec{\theta})}} \prod_{i=1}^{N} \frac{\mu s f_s(\vec{x}_i; \vec{\theta}) + b f_b(\vec{x}_i; \vec{\theta})}{b f_b(\vec{x}_i; \vec{\theta})} =$$

$$= e^{-\mu s(\vec{\theta})} \prod_{i=1}^{N} \left(\frac{\mu s f_s(\vec{x}_i; \vec{\theta})}{b f_b(\vec{x}_i; \vec{\theta})} + 1 \right).$$

$$-\log \lambda(\mu, \vec{\theta}) = \mu s(\vec{\theta}) - \sum_{i=1}^{N} \log \left(\frac{\mu s f_s(\vec{x}_i; \vec{\theta})}{b f_b(\vec{x}_i; \vec{\theta})} + 1 \right).$$

Applying Wilk's theorem to searches test statistic

 In case of counting experiment f_s and f_b terms are dropped and the expression simplifies to

$$\begin{split} \lambda(\vec{\theta}\,) &= \frac{e^{-(\mu s(\vec{\theta}\,) + b(\vec{\theta}\,))} (\,\mu s(\vec{\theta}\,) + b(\vec{\theta}\,))^N}{N!} \frac{N!}{e^{-b(\vec{\theta}\,)} b(\vec{\theta}\,)^N} = \\ &= e^{-\mu s(\vec{\theta}\,)} \left(\frac{\mu s(\vec{\theta}\,)}{b(\vec{\theta}\,)} + 1 \right)^N \; . \\ &- \log \lambda(\vec{\theta}\,) = \mu s(\vec{\theta}\,) - N \log \left(\frac{\mu s(\vec{\theta}\,)}{b(\vec{\theta}\,)} + 1 \right) \; , \end{split}$$

Example datacard for counting experiment

```
imax 1
jmax 2
kmax 3
# A single channel - ch1 - in which 0 events are observed in data
bin
            ch1
observation
bin
           ch1
                ch1
                     ch1
process ppX
                 WW tt
process
           1.47 0.64
                      0.22
rate
# -----
lumi lnN 1.11 1.11
                      1.11
xs lnN 1.20
nWW gmN 4 - 0.16
```

Example datacard for template shapes analysis

```
imax 1
jmax 1
kmax 4
shapes * * template-analysis-datacard-input.root $PROCESS

→ $PROCESS $SYSTEMATIC

          ch1
bin
observation 85
bin
          ch1
                        ch1
process signal background
process
rate
                        100
lumi lnN 1.1
                    1.0
bgnorm lnN
                   1.3
alpha
      shape
                           # uncertainty in the background template.
sigma
      shape
              0.5
                           # uncertainty in the signal template.
```

BONUS: CMS higgs observation statistical analysis

- Exit container and check container name
 - o Ctrl+D
 - docker container is --all # find the name of your container

```
→ hep_lectures docker container ls --all

CONTAINER ID IMAGE

COMMAND

COMMAND

COMMAND

COMMAND

COMMAND

COMMAND

COMMAND

CREATED

STATUS

PORTS

NAMES

COMMAND

CREATED

STATUS

PORTS

NAMES

Compassionate_keldysh

a735F8717912

gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1

7d8a506d58ec

gitlab-registry.cern.ch/cms-cloud/combine-standalone:v9.2.1

T/bin/bash -1 -c /bi...

3 hours ago

Exited (127) 5 minutes ago

optimistic_kepler

dazzling_jennings
```

- Copy datacards into container
 - wget
 <u>https://repository.cern/records/c2948-e8875/files/cms-h-observation-public-v1.0.tar.gz\?download\=1</u>
 - o mv cms-h-observation-public-v1.0.tar.gz\?download=1 cms-h-observation-public-v1.0.tar.gz
 - docker container cp cms-h-observation-public-v1.0.tar.gz \

 container_name>:/code/HiggsAnalysis/CombinedLimit
 - docker container restart <container_name>
 - docker container attach <container name>
 - o tar zxvf cms-h-observation-public-v1.0.tar.gz
- Podman has equivalent commands

Домашне завдання

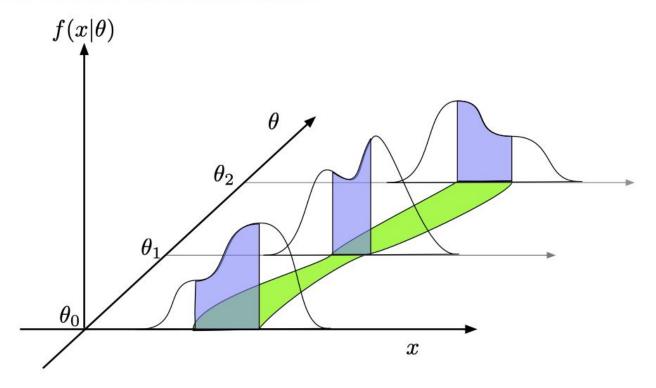
- Створити власну карту для counting experiment
 - Одине джерело фонових подій + сигнал

- Порівняти результати
 - LEP, TEVATRON, LHC upper limits
 - Для різних рівнів фонових подій

BACKUP

NEYMAN CONSTRUCTION EXAMPLE

This makes a **confidence belt** for heta



<u>Neyman construction — Statistics and Data Science (theoryandpractice.org)</u>

A RESTATEMENT OF THE CONSTRUCTION

For every point θ , if it were true, the data would fall in its acceptance region with probability $1-\alpha$

If the data fell in that region, the point θ would be in the interval So the interval $[\theta_-, \theta_+]$ covers the true value with probability $1 - \alpha$

