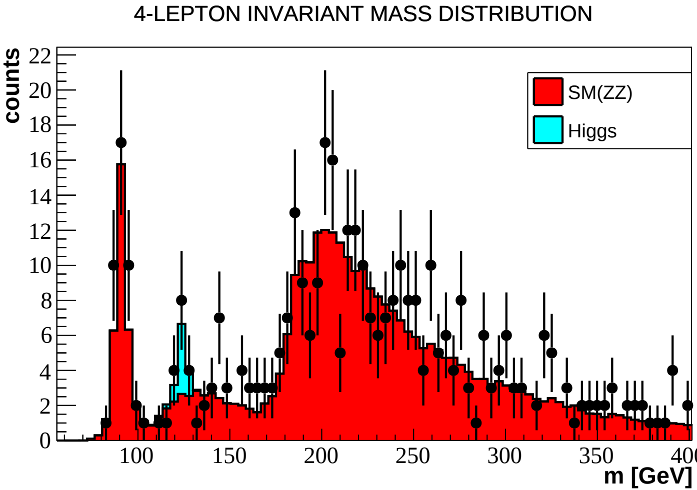
Search for Higgs boson in 4-muon final state

Federico Nardi

Presentation for

Data Analysis in High Energy Physics

1



4-LEPTON INVARIANT MASS DISTRIBUTION
counts
0
2
4
6
8
10
12
14
16
18
20
22
100
150
200
250
300
350
400
m [GeV]
SM(ZZ)
Higgs

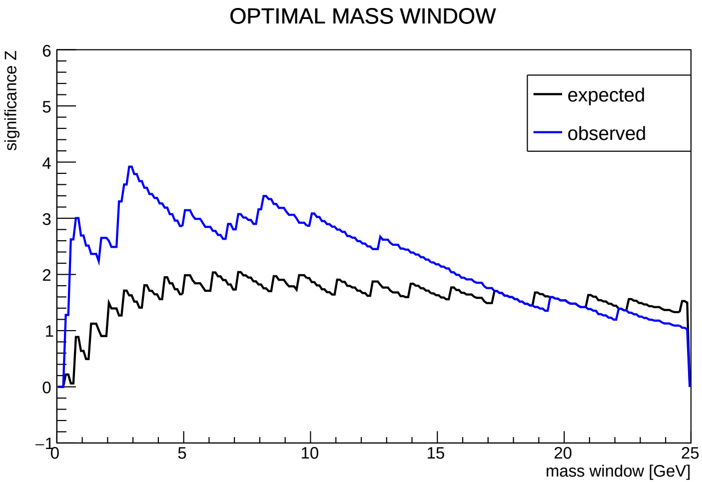
Hypothesis testing

- REJECTING hypothesis
- choose test statistic t
- hypotheses $H_i \; (i = 1, 2, \ldots)$
- p-values $p_i := \int_{t_{obs}}^{+\infty} g(t|H_i)dt$
- significance $Z(p) = \Phi^{-1}(1 - p)$
- $H_0, H_1 \rightarrow$ background: 5σ, signal: $CL_{s+b} \rightarrow CL_s < 0.05$

Significance optimization

- testing b-only hypothesis
- $t \rightarrow n$: counts in a mass window $\Rightarrow$ Poisson
- How large?
- significance: Expected vs Observed

Significance optimization



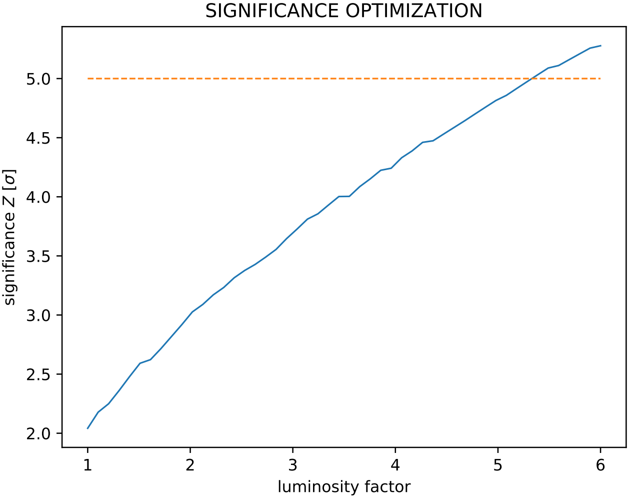
Significance optimization

	width [GeV]	Z
expected	7.15	2.04
observed	2.85	3.91

Table: Optimal mass window and significance for expected and observed significance

- increasing luminosity

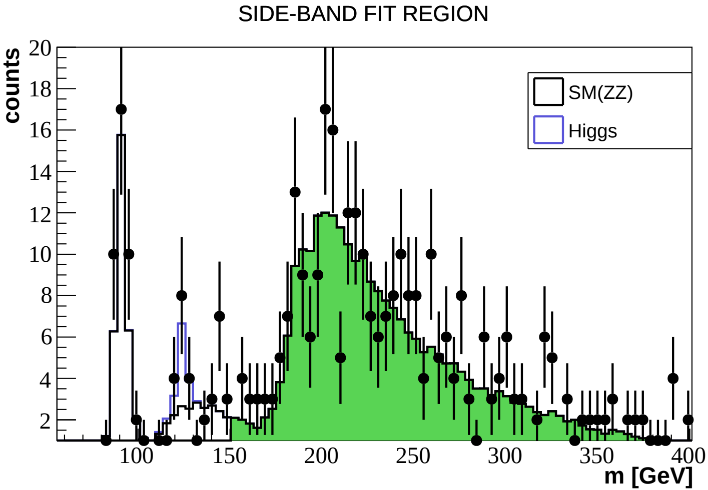
Significance optimization



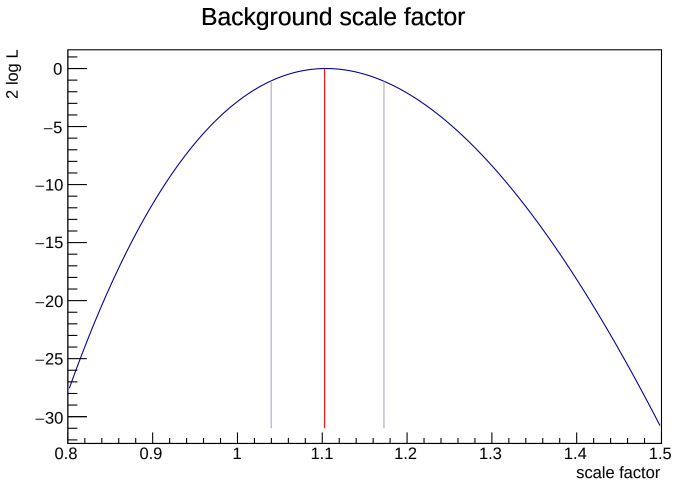
Parameter estimation - MLE

- event distribution: $f_{s+b} = \alpha \, f_{SM} + \mu \, f_{Higgs}$
- $\mathscr{L}(\boldsymbol{\theta}) := \prod_{i=1}^{N_{tot}} f(n_i|\boldsymbol{\theta}) \rightarrow$ ideal $\hat{\boldsymbol{\theta}}$
- Can also get (approx, gaussian) 1σ limits

Parameter estimation - Side-Band fit



Parameter estimation - Side-Band fit



Parameter estimation - Side-Band fit

The fitted background scale factor turns out to be

$$\alpha_{bgr} = 1.10^{+0.07}_{-0.06}$$

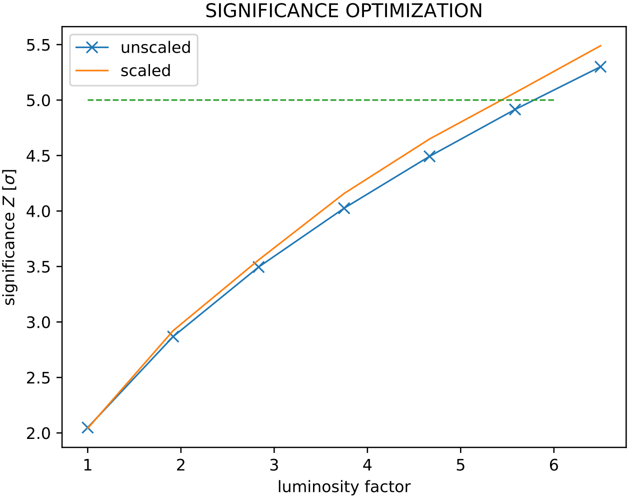
This leads to a scaling in the number of background events in the optimal 7.15GeV window around the signal peak:

$$N_{bgr} = 4.64 \qquad \rightarrow \qquad N_{bgr} = 5.12^{+0.32}_{-0.29}.$$

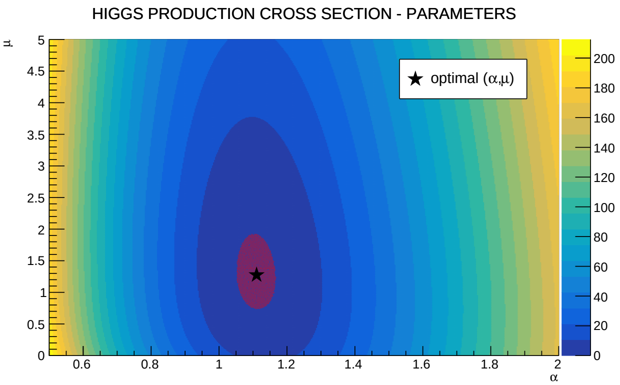
In the same interval we expect $N_{sig} = 5.41$ signal events, and the observed events are $N_{obs} = 13$

- Calculate again significance. 10^6 MC cycles

Parameter estimation - Side-Band fit



Parameter estimation - signal and background scalefactors

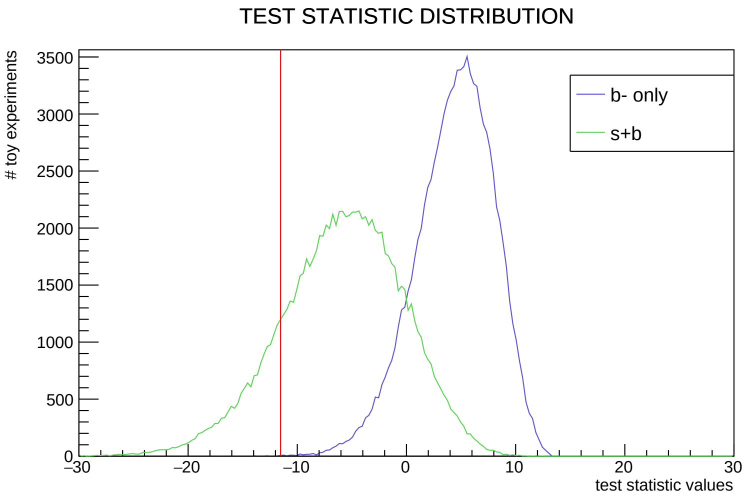


$$\mu_s = 1.28^{+0.65}_{-0.53} \qquad \alpha_{bgr} = 1.10^{+0.07}_{-0.06}.$$

Profile likelihood test statistic

- Neyman-Pearson lemma. Simple hypotheses
- $\lambda(x) = \frac{\mathscr{L}(x|H_1)}{\mathscr{L}(x|H_0)} \rightarrow \Lambda = -2\log(\lambda)$
- 10^6 toy datasets for H_0, H_1

Profile likelihood test statistic



Profile likelihood. Discovery

	Λ_{obs}	CL_{sb}	p_0	Z [σ]
b-only	4.78	0.516	0.484	0.03
s+b	-5.69	0.993	0.007	2.46
data	-11.53	0.99988	1.2×10^{-4}	3.67

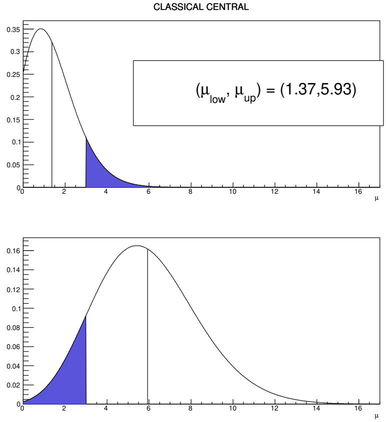
Table: b-only hypothesis. p-values and confidence levels for average b-only, average s+b experiments and measured value of Λ.

Profile likelihood. Exclusion

	CL_b	p_1	CL_s
b-only	0.021	0.979	0.040
s+b	0.505	0.495	0.508
data	0.848	0.152	0.848

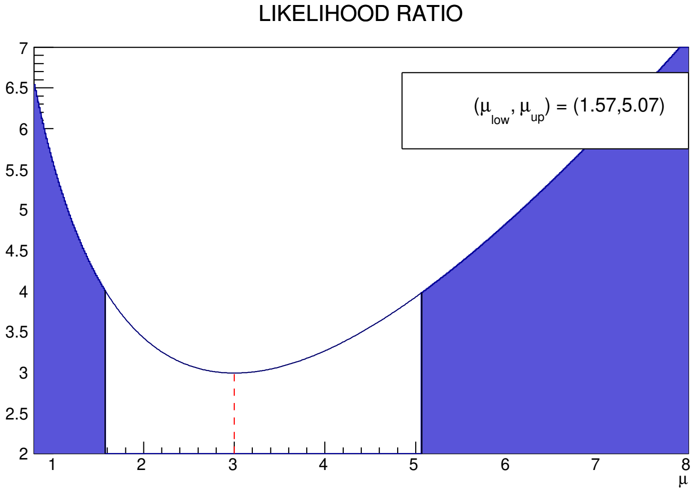
Table: s+b hypothesis. p-values and confidence levels for average b-only, average s+b experiments and measured value of Λ.

1σ CL intervals



- $\sqrt{n_{obs}} \rightarrow$ not true mean
- $\sum_{n=n_{obs}}^{+\infty} P(n|\mu_{low}) = 16\%$
- $\sum_{n=0}^{n_{obs}} P(n|\mu_{up}) = 16\%$

1σ CL intervals



1σ CL intervals

Use Bayes' theorem

$$P(\mu|n_o)d\mu = \frac{\mathscr{L}(n_o|\mu)\pi(\mu)d\mu}{\int_{D(\mu')}\mathscr{L}(n_o|\mu')\pi(\mu')d\mu'}.$$

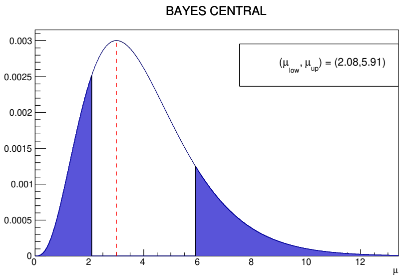
If we then use a uniform prior in our domain $D(\mu)$

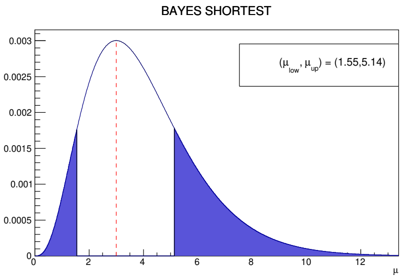
$$\pi(\mu) = \text{const} \qquad \forall\mu \in D(\mu)$$

all the extra calculations are reduced to an overall normalization constant and we can write

$$P(\mu|n_o) \propto \mathscr{L}(n_o|\mu) \tag{1}$$

1σ CL intervals





Thank you!