Latest CDF Higgs Results and Combined Higgs Limits

Nils Krumnack (Baylor University)
Introduction

• this seminar falls into two parts
• in the first part I will give an overview of CDF Standard Model Higgs result
• in the second part I will explain the details of our Bayesian limit calculation

• not covering:
• details of the experiments and accelerator
• beyond standard model Higgs results
• Production modes very similar between Tevatron and LHC (http://maltoni.home.cern.ch/maltoni/TeV4LHC/SM.html)
• one exception: Tevatron has more associated Higgs
• particularly clean event signature
• used in most Tevatron searches
Higgs Decay

- Higgs has many choices to decay
- main decay modes: $bb$ and $WW$
- $gg \rightarrow H \rightarrow WW$: sensitive channel
- $gg \rightarrow H \rightarrow bb$: huge backgrounds
- can use associated production ($WH/ZH$) for better s/b in $bb$
- alternatives: $\tau\tau$ and $\gamma\gamma$ have lower backgrounds, but also lower branching ratio
common techniques

• lepton id: leptons are a part of most Higgs final states
• leptons are easy to identify and trigger on
• only few backgrounds have leptons
• most channels work on looser lepton id

• b-tagging: identifies jets from b quarks
• essential for low mass channels
• uses displaced vertices
   (and soft leptons from b decays)
• divide sample into several tag categories
  (different s/b)
• somewhat difficult to calibrate/model
common techniques

• missing transverse energy: part of many Higgs final states
• only few backgrounds, but many fakes from multi-jet events
• can be triggered on (at the Tevatron)

• neural networks (NN) and boosted decision trees (BDT)
• trained on Monte Carlo samples for signal and background
• provides event discriminant for every single event
• pulls apart high from low s/b regions

• matrix element calculates event discriminant from LO ME and detector resolution functions
• calculates differential rate for the topology of each event for signal and major backgrounds
• output normally fed into a NN or BDT
\[ H \rightarrow WW \rightarrow l\nu l\nu \]

- the main Higgs search channel
- most sensitive channel down to \( m_H = 125 \)
- branching ratio at 125 is only 20%

- accepts events from all the production modes
- including \( gg \rightarrow H \)
- possible through clean WW signature

- innovations: looser lepton ID
- accepting leptons in many categories
H → WW → ℓνℓν

• separate analysis for 0, 1 & 2 jets
• different signal and background
• allows for ZH, WH and VBF events

• uses ME and NN for the event discriminant
H→WW→lνlν

- train a separate neural network for each mass and each number of jets
- extract limit from NN output distributions
- most sensitive around m_H=165 GeV
- observed (expected) limit at 165 GeV: 1.72 (1.62)
• the other high mass analysis
• more than 10 times less sensitive than the WW result
• requires two same sign leptons, vetoes on third lepton
• uses BDT for signal discrimination
• currently optimized for fermiophobic Higgs, working on update with better sensitivity for SM Higgs
WH→lνbb

- most sensitive channel for low mass
- identifies W through a lepton and missing transverse energy
- identifies H as dijet pair with b-tags
- divides data into lepton and b-tag categories

- adds lepton acceptance with very loose, stub-less muons
- these are not triggered directly
- use MET+dijet trigger instead
  - muons look like MET in trigger
- QCD background surprisingly low
• train separate discriminants one with ME+BDT and one with NN
• combine both into a superdiscriminant using an evolutionary NN
• obs (exp) limit @115: 5.6 (4.8)
ZH → ννbb

- also a sensitive channel for low mass
- identifies H as two b-tagged jets
- identifies Z as missing transverse energy
- also picks up WH with missing lepton
  - allows third jet for this

- main background are multi-jet events
- no real missing energy, but a lot through jet missmeasurement
- cleaned up by comparing tracking and calorimeter missing energy
- correlated for true missing energy
$\text{ZH} \rightarrow \nu \nu b b$

- train a NN to distinguish signal from multi-jet background
- cut on NN value
- train new NN to distinguish from other backgrounds
- extract limit from that NN output distribution

- $\text{obs (exp) limit @115: 6.9 (5.6)}$
ZH→llbb

- third most sensitive channel at low mass
- identifies H through two b-tagged jets
- identifies Z through two leptons with invariant mass at Z peak
- extends lepton acceptance through extra loose id

- events contain no true missing energy
- all missing energy from jet missmeasurements
- improving jet resolution by correcting jets for observed missing energy
ZH → llbb

- train a 2d NN to discriminate against 2 backgrounds
- limit extracted from 2d distribution in several tag and lepton categories
- obs (exp) limit @115: 7.1 (9.9)
H → ττ

• only search for SM Higgs in the ττ decay mode at a hadron collider
• contributes 10% to the final limit
• looks for one hadronic and one leptonic tau
• requires two additional jets
• accepts events from all the production modes
• including gg → H and VBF
• train 3 NN to distinguish signal from top, QCD and Z background
• use minimum of NN discriminants as event discriminant

• observed (expected) limits at 115: 30.5 (24.8)
• heroic attempt to search for Higgs using only jets
• not in current combination, hopefully in next

• identify H as two b-tagged jets
• identify W/Z as two more jets
• main problem: background modeling

• using ME discriminant
• obs (exp) limit @115: 37.5 (36.8)
Channel Plot

CDF Run II Preliminary, L=2.0-3.0 fb⁻¹

LEP Excl.

95% CL Limit/SM

SM

LEP

WWW 2.7 fb⁻¹ Obs
WWW 2.7 fb⁻¹ Exp
H→ττ 2.0 fb⁻¹ Obs
H→ττ 2.0 fb⁻¹ Exp
ZH→llbb 2.7 fb⁻¹ Obs
ZH→llbb 2.7 fb⁻¹ Exp

WH+ZH→bbMET 2.1 fb⁻¹ Obs
WH+ZH→bbMET 2.1 fb⁻¹ Exp
WH→lνbb 2.7 fb⁻¹ Obs
WH→lνbb 2.7 fb⁻¹ Exp
H→WW 3.0 fb⁻¹ Obs
H→WW 3.0 fb⁻¹ Exp
Combined Obs
Combined Exp

CDF Higgs Results and Combination
Nils Krumnack (Baylor University)
Combination Plot

CDF Run II Preliminary, L=2.0-3.0 fb⁻¹

95% CL Limit/SM

LEP Limit

Expected

- Observed

±1σ

±2σ

m_H (GeV/c²)

January 15, 2009
**m_H=160 GeV**

- most sensitive mass point overall
- really just H→WW
- observed limit: \( \sigma = 1.56 \times \text{SM} \)
- expected limit: \( \sigma = 1.75 \times \text{SM} \)
m_H=160 GeV

- most sensitive mass point overall
- really just H \rightarrow WW
- observed limit: σ = 1.56 * SM
- expected limit: σ = 1.75 * SM

these plots will be explained on future slides
m_H = 160 GeV

- most sensitive mass point overall
- really just H → WW

- observed limit: σ = 1.56 * SM
- expected limit: σ = 1.75 * SM

this plot compares data to signal and background shapes

combines bins of similar s/b

CDF Run II Preliminary, L=2.7-3.0 fb⁻¹

Mean 0.5956
RMS 0.4901
χ² / ndf 73.87 / 67
Prob 0.2639
p0 3836 ± 1502.0
p1 0.5946 ± 0.1031
p2 2.815 ± 0.732
p3 3.027 ± 0.369
m_H = 160 GeV

• most sensitive mass point overall
• really just H → WW

• observed limit: \( \sigma = 1.56 \times \text{SM} \)
• expected limit: \( \sigma = 1.75 \times \text{SM} \)

Compares past and present expected limits scaled by \( \sqrt{2} \) for Tevatron expectation.

Uses \( 1/\sqrt{L} \) scaling with luminosity.

Band anticipates future improvements.
m_H = 160 GeV

- most sensitive mass point overall
- really just H → WW

- observed limit: \( \sigma = 1.56 \times \text{SM} \)
- expected limit: \( \sigma = 1.75 \times \text{SM} \)
CDF Higgs Results and Combination

Nils Krumnack (Baylor University)

- **$m_H = 115$ GeV**

- Most sensitive low mass point above LEP exclusion
  - Observed limit: $\sigma = 3.76 \times \text{SM}$
  - Expected limit: $\sigma = 3.17 \times \text{SM}$
Limit Calculation

• the limit calculation is done in a purely bayesian framework
• for the Tevatron combination we compared it with a frequentist calculation and found agreement within 10%

• for the combined limit we take all results back to the stage of data histograms and signal and background templates
• the limit is calculated from this in a single step

• on the following pages, I will explain how:
  • first for a single bin counting experiment
  • then for a combination of bins
  • finally how to incorporate systematic error
Bayesian vs. Frequentist

• what is the difference between Bayesian and Frequentist?
• simple example: what does $m_{\text{top}} = 172.4 \pm 1.2$ mean?

• Bayesian answer:
  • we believe the mass of the top to be between 171.2 and 173.6 with 68% probability (credibility)

• Frequentist answer:
  • No, No, you can’t do/say that!
  • either the mass is in that range or it is not
  • you can’t assign a probability just because you don’t know
  • we say that our experiment set the mass range 171.2-173.6
  • we know that if we repeated the experiment many times it would include the right value 68% of the time (coverage)
Counting Experiments

• A counting experiment consists of simply counting events
• Equivalent to a single histogram bin

• Need some definitions now:
• n: the observed number of events
• b: the expected number of background
• s: the assumed expected number of signal events
  ‣ True value unknown
• \( L(n;s) \): the likelihood (probability) of observing n events giving an expected signal of s

• For counting experiments we use Poisson statistics:
• \( L(n;s) = \text{pois}(n,s+b) = c \cdot (s+b)^n \cdot e^{-(s+b)} \)
Bayesian Posterior

• try to calculate the (posterior) probability $p(s;n)$ of having a true expected signal of $s$, when observing $n$ events

• exploit Bayes theorem:
  
  $$p(s;n) = L(n;s) \cdot P_s(s)/P_n(n)$$

• we are missing the functions $P_s$ and $P_n$:
  
  • $P_s$ is unknown and interpreted as the (prior) probability of an expected signal $s$ before the measurement
    ‣ arbitrarily choose it to be flat ($1$ for $s \geq 0$, $0$ for $s < 0$)
  • $P_n$ is unknown, but constant for any $n$
    ‣ only affects normalization: $p(s;n) = c_n \cdot L(n;s)$

• normalize $p(s;n)$ as probability: $\int p(s;n)ds = 1$
Observed Limits

- a 95% confidence interval $R$ has the property:
  - $\int_{R} p(s;n)ds = 0.95$
- can choose $R$ arbitrarily
  - can choose to cover the maximum values of $p(s;n)$
  - can choose to leave 2.5% uncovered on each end
  - for upper limits choose a range starting at 0: $R = [0, x]$
    - $x$ is then the 95% limit
- $x$ depends on the choice of $P_s$
  - e.g.: choosing $P_s$ flat in $\ln(s)$ would give a different result

CDF Run II Preliminary, $L=2.7-3.0 \text{ fb}^{-1}$

Mean 0.5956
RMS 0.4901

$m_H = 160$
Expected Limits

- expected limits show the sensitivity of the experiment
- they do not take the observed events into account at all
- based on pseudo-experiments (PE) with 0 signal

- run complete limit calculation on each PE
- plot the obtained limits for a large number of PEs
- take the median as the expected limit
- take quantiles 2%, 16%, 84% and 98% as borders for 1 & 2σ bands
- bands not to be mistaken for errors

- excess of observed limit (red) would be sign of Higgs
- slice through limit vs. mass plot

CDF Run II Preliminary, L=2.0-3.0 fb⁻¹

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3.412</td>
</tr>
<tr>
<td>RMS</td>
<td>1.241</td>
</tr>
<tr>
<td>χ²/ndf</td>
<td>58.4 / 64</td>
</tr>
<tr>
<td>Prob</td>
<td>0.6739</td>
</tr>
<tr>
<td>p0</td>
<td>577.5 ± 171.2</td>
</tr>
<tr>
<td>p1</td>
<td>0.9992 ± 0.1833</td>
</tr>
<tr>
<td>p2</td>
<td>2.834 ± 0.719</td>
</tr>
<tr>
<td>p3</td>
<td>1.611 ± 0.193</td>
</tr>
</tbody>
</table>

mₜ=115
Multi-Bin Limit

• we rarely do counting experiments anymore…
• in reality use histograms for data and signal and background expectation
• every histogram bin interpreted as a counting experiment

• individual likelihood per bin: \( L_i(n_i; s) = \text{pois}(n_i, s \cdot s_i + b_i) \)
• \( n_i \) and \( b_i \) correspond to the \( n \) and \( b \) for single bin
• \( s_i \) is the relative signal acceptance for each bin

• overall likelihood is defined as
  \[ L(n_0, n_1, \ldots; s) = L_0(n_0; s) \cdot L_1(n_1; s) \]
• from there everything goes as before
• PEs consist of the numbers \( n_i \), generated independently
• also works when combining several histograms
Nuisance Parameters

• I have not yet described the incorporation of systematic uncertainties.
• Ignoring them is unrealistic.

• Simple example: assume we have a 10% error on b.
• Handle it by introducing a nuisance parameter x.
• Redefine likelihood: \( L(n; s, x) = \text{pois}(n, s + b \cdot (1 + 0.1 \cdot x)) \)

• However: likelihood is not complete.
• Somebody measured the 10% error on b.
• His likelihood is: \( L_x(n; s, x) = \text{gaus}(x) \)

• Overall combined likelihood: \( L'(n; s, x) = L(n; s, x) \cdot L_x(n; s, x) \)
Prior Probabilities

• recall: \( p(s,x;n) = c \cdot L'(n;s,x) \cdot P(s) \)
• \( P(s) \) is the prior probability, assumed flat

• now we can restructure:
• \( p(s,x;n) = c \cdot L'(n;s,x) \cdot P(s) = c \cdot L(n;s,x) \cdot \text{gaus}(x) \cdot P(s) \)
• define: \( P'(s,x) = \text{gaus}(x) \cdot P(s) \)
• \( p(s,x;n) = c \cdot L(n;s,x) \cdot P'(s,x) \)

• \( P'(s,x) \) is the new prior probability
• now incorporates all our prior knowledge on \( x \)
• can be easily extended to a large number of systematics
Limits With Systematics

• we are stuck with a 2d posterior now: \( p'(s,x;n) \)
• need to get back to 1d for calculating the limit
• could calculate limit as function of \( x \) (like we do for \( m_H \))

• however: we are doing Bayesian calculations
• as such, we can combine different hypotheses
• can just add up all the different hypotheses for a given \( s \)
• do that by integrating over \( x \): \( p''(s;n) = \int p'(s,x;n)dx \)

• for pseudo-experiments pick nuisance parameters randomly according to prior probabilities
• means that every pseudo-experiment happens at a different point in nuisance parameter space
Putting It Together

• expected entries in each bin:
  \[ S_{ij}(x_0,x_1,\ldots)=s_{ij} \cdot \prod_k (1+y_{ijk} \cdot x_k) \]
  \[ B_{ij}(x_0,x_1,\ldots)=b_{ij} \cdot \prod_k (1+z_{ijk} \cdot x_k) \]

• \( y_{ijk} \) and \( z_{ijk} \) are the fractional errors in bin \( i \) for systematic \( k \) and template \( j \)

• likelihood per bin: \( L_i(n_i;s,x_0,x_1,\ldots)=\text{pois}(n_i, s \cdot \prod S_{ik} + \prod B_{ik}) \)

• prior probability: \( P(s,x_0,x_1,\ldots)=\prod_k \text{gaus}(x_k) \)

• posterior probability:
  \[ p(s,x_0,x_1,\ldots;n_0,n_1,\ldots)=P(s,x_0,x_1,\ldots) \prod L_i(n_i;s,x_0,x_1,\ldots) \]
  \[ p'(s;n_0,n_1,\ldots)=\int \int \int p(s,x_0,x_1,\ldots;n_0,n_1,\ldots)dx_0dx_1\ldots \]

• calculate 95% limit \( A \) as: \( \int^Ap'(s;n_0,n_1,\ldots)=0.95 \)
templates derived from data events or Monte Carlo
limited statistics lead to statistical errors on templates
assign a statistical error to each $s_{ij}$ and $b_{ij}$
integrate over the statistical errors with extra nuisance parameters for each bin

can also use posteriors to perform measurements
the mean and RMS correspond to the measured value and its error
similar to fitting, but more stable (and slower)

only thing left: calculating the integral
can be done by Monte Carlo integration
in a few hundred/thousand dimensions…
Markov Chain MC

- Monte Carlo integration method
- Improvement on scattershot MC
- Faster and more stable results

- Problem: most integration points contribute little
- Would like to sample only the peaks of the distribution
- Problem: we throw nuisance parameters, not likelihood

- Solution: we slowly walk along the peaks taking care not to step into the valley
  - Markov Chain Monte Carlo
Markov Chain MC

- commonly used for Bayesian integrals in high dimensions
- creates a sequence of integration points
  - relative frequency is according to relative weights
  - individual points can be repeated
- starts from a random point and run until it reaches the stationary distribution

- using Metropolis-Hastings algorithm
- at each point use a (gaussian) proposal function to select a nearby point \( x \)
- compare weights:
  - \( \text{new/old} > 1 \): move to new point
  - \( \text{new/old}=p \): move to new point with probability \( p \)
Summary and Outlook

- presented an overview of CDF Higgs results
- showed the latest CDF Higgs combination

- provided an introduction into Bayesian limit calculation
- did not explain all the details that go into preparing the inputs for the combination (the main part of the work)

- expect that we combine the CDF results with D0 results for the Winter conferences
- should hopefully show a nice exclusion region at high mass
- also working on combining MSSM Higgs limits
backup slides
## Signal Cross Sections

<table>
<thead>
<tr>
<th>$m_H$ (GeV/$c^2$)</th>
<th>$\sigma_{gg\to H}$ (fb)</th>
<th>$\sigma_{WH}$ (fb)</th>
<th>$\sigma_{ZH}$ (fb)</th>
<th>$\sigma_{VBF}$ (fb)</th>
<th>$B(H \to bb)$ (%)</th>
<th>$B(H \to \tau^+\tau^-)$ (%)</th>
<th>$B(H \to W^+W^-)$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1689.9</td>
<td>286.1</td>
<td>166.7</td>
<td>99.5</td>
<td>81.21</td>
<td>7.924</td>
<td>1.009</td>
</tr>
<tr>
<td>105</td>
<td>1497.1</td>
<td>244.6</td>
<td>144.0</td>
<td>93.3</td>
<td>79.57</td>
<td>7.838</td>
<td>2.216</td>
</tr>
<tr>
<td>110</td>
<td>1332.0</td>
<td>209.2</td>
<td>124.3</td>
<td>87.1</td>
<td>77.02</td>
<td>7.656</td>
<td>4.411</td>
</tr>
<tr>
<td>115</td>
<td>1188.1</td>
<td>178.8</td>
<td>107.4</td>
<td>79.07</td>
<td>73.22</td>
<td>7.340</td>
<td>7.974</td>
</tr>
<tr>
<td>120</td>
<td>1057.5</td>
<td>152.9</td>
<td>92.7</td>
<td>71.65</td>
<td>67.89</td>
<td>6.861</td>
<td>13.20</td>
</tr>
<tr>
<td>125</td>
<td>945.4</td>
<td>132.4</td>
<td>81.1</td>
<td>67.37</td>
<td>60.97</td>
<td>6.210</td>
<td>20.18</td>
</tr>
<tr>
<td>130</td>
<td>847.8</td>
<td>114.7</td>
<td>70.9</td>
<td>62.5</td>
<td>52.71</td>
<td>5.408</td>
<td>28.69</td>
</tr>
<tr>
<td>135</td>
<td>762.0</td>
<td>99.3</td>
<td>62.0</td>
<td>57.65</td>
<td>43.62</td>
<td>4.507</td>
<td>38.28</td>
</tr>
<tr>
<td>140</td>
<td>687.5</td>
<td>86.0</td>
<td>54.2</td>
<td>52.59</td>
<td>34.36</td>
<td>3.574</td>
<td>48.33</td>
</tr>
<tr>
<td>145</td>
<td>621.3</td>
<td>75.3</td>
<td>48.0</td>
<td>49.15</td>
<td>25.56</td>
<td>2.676</td>
<td>58.33</td>
</tr>
<tr>
<td>150</td>
<td>563.4</td>
<td>66.0</td>
<td>42.5</td>
<td>45.67</td>
<td>17.57</td>
<td>1.851</td>
<td>68.17</td>
</tr>
<tr>
<td>155</td>
<td>511.5</td>
<td>57.8</td>
<td>37.6</td>
<td>42.19</td>
<td>10.49</td>
<td>1.112</td>
<td>78.23</td>
</tr>
<tr>
<td>160</td>
<td>460.7</td>
<td>50.7</td>
<td>33.3</td>
<td>38.59</td>
<td>4.00</td>
<td>0.426</td>
<td>90.11</td>
</tr>
<tr>
<td>165</td>
<td>409.3</td>
<td>44.4</td>
<td>29.5</td>
<td>36.09</td>
<td>1.265</td>
<td>0.136</td>
<td>96.10</td>
</tr>
<tr>
<td>170</td>
<td>367.6</td>
<td>38.9</td>
<td>26.1</td>
<td>33.58</td>
<td>0.846</td>
<td>0.091</td>
<td>96.53</td>
</tr>
<tr>
<td>175</td>
<td>333.4</td>
<td>34.6</td>
<td>23.3</td>
<td>31.11</td>
<td>0.663</td>
<td>0.072</td>
<td>95.94</td>
</tr>
<tr>
<td>180</td>
<td>303.1</td>
<td>30.7</td>
<td>20.8</td>
<td>28.57</td>
<td>0.541</td>
<td>0.059</td>
<td>93.45</td>
</tr>
<tr>
<td>190</td>
<td>247.8</td>
<td>24.3</td>
<td>16.6</td>
<td>24.88</td>
<td>0.342</td>
<td>0.038</td>
<td>77.61</td>
</tr>
<tr>
<td>200</td>
<td>207.3</td>
<td>19.3</td>
<td>13.5</td>
<td>21.19</td>
<td>0.260</td>
<td>0.029</td>
<td>73.47</td>
</tr>
</tbody>
</table>
# Limit Values

<table>
<thead>
<tr>
<th>$m_H$ (GeV/$c^2$)</th>
<th>Observed limit/SM</th>
<th>$-2\sigma$ expected</th>
<th>$-1\sigma$ expected</th>
<th>median expected</th>
<th>$+1\sigma$ expected</th>
<th>$+2\sigma$ expected</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2.70</td>
<td>1.42</td>
<td>1.87</td>
<td>2.63</td>
<td>3.77</td>
<td>5.33</td>
</tr>
<tr>
<td>105</td>
<td>2.58</td>
<td>1.46</td>
<td>1.93</td>
<td>2.65</td>
<td>3.66</td>
<td>4.99</td>
</tr>
<tr>
<td>110</td>
<td>3.50</td>
<td>1.48</td>
<td>2.03</td>
<td>2.88</td>
<td>4.07</td>
<td>5.62</td>
</tr>
<tr>
<td>115</td>
<td>3.76</td>
<td>1.62</td>
<td>2.21</td>
<td>3.17</td>
<td>4.54</td>
<td>6.36</td>
</tr>
<tr>
<td>120</td>
<td>4.10</td>
<td>2.06</td>
<td>2.71</td>
<td>3.72</td>
<td>5.13</td>
<td>6.97</td>
</tr>
<tr>
<td>125</td>
<td>4.91</td>
<td>2.13</td>
<td>2.82</td>
<td>3.89</td>
<td>5.41</td>
<td>7.41</td>
</tr>
<tr>
<td>130</td>
<td>4.67</td>
<td>2.15</td>
<td>2.93</td>
<td>4.12</td>
<td>5.80</td>
<td>8.00</td>
</tr>
<tr>
<td>135</td>
<td>4.26</td>
<td>2.01</td>
<td>2.70</td>
<td>3.82</td>
<td>5.43</td>
<td>7.58</td>
</tr>
<tr>
<td>140</td>
<td>4.11</td>
<td>1.94</td>
<td>2.60</td>
<td>3.61</td>
<td>5.02</td>
<td>6.86</td>
</tr>
<tr>
<td>145</td>
<td>3.96</td>
<td>1.85</td>
<td>2.52</td>
<td>3.50</td>
<td>4.84</td>
<td>6.55</td>
</tr>
<tr>
<td>150</td>
<td>3.48</td>
<td>1.51</td>
<td>1.95</td>
<td>2.70</td>
<td>3.78</td>
<td>5.24</td>
</tr>
<tr>
<td>155</td>
<td>2.50</td>
<td>1.26</td>
<td>1.68</td>
<td>2.34</td>
<td>3.29</td>
<td>4.54</td>
</tr>
<tr>
<td>160</td>
<td>1.56</td>
<td>0.92</td>
<td>1.24</td>
<td>1.75</td>
<td>2.47</td>
<td>3.43</td>
</tr>
<tr>
<td>165</td>
<td>1.76</td>
<td>0.91</td>
<td>1.23</td>
<td>1.72</td>
<td>2.41</td>
<td>3.32</td>
</tr>
<tr>
<td>170</td>
<td>2.05</td>
<td>1.09</td>
<td>1.45</td>
<td>2.01</td>
<td>2.80</td>
<td>3.85</td>
</tr>
<tr>
<td>175</td>
<td>2.12</td>
<td>1.30</td>
<td>1.78</td>
<td>2.50</td>
<td>3.48</td>
<td>4.75</td>
</tr>
<tr>
<td>180</td>
<td>2.88</td>
<td>1.51</td>
<td>2.14</td>
<td>3.02</td>
<td>4.20</td>
<td>5.69</td>
</tr>
<tr>
<td>190</td>
<td>5.57</td>
<td>2.52</td>
<td>3.32</td>
<td>4.61</td>
<td>6.44</td>
<td>8.85</td>
</tr>
<tr>
<td>200</td>
<td>9.98</td>
<td>3.39</td>
<td>4.54</td>
<td>6.33</td>
<td>8.85</td>
<td>12.14</td>
</tr>
</tbody>
</table>
s/b integrated

- corresponds to sliding a cut on the s/b for a counting experiment
- note that the data points are correlated
• solely based on extrapolation of expected limits
• not taking data collected so far into account
p values

• used if you actually want to discover something
• run background only PEs
• p value is the fraction of PEs are more signal like than the observation
• low p value corresponds to discovery

• could use observed limit here
• however there are better observables
• best observable: ratio of likelihood of signal+background and background-only hypothesis