



ATLAS Discovery Experience

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On behalf of ATLAS

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Outline

- Combination Procedure
- Asymptotic Limit Bands
- Low count $\hat{\mu}$ / Physical PDF
- P-Value Uncapping
- Asymmetric Uncertainty Handling

Combination Procedure

- Individual models (likelihoods, datasets, etc) provided by subgroups electronically via RooFit workspaces

- Start with the individual likelihoods $\mathcal{L}_i(\mu, \theta_i) = \mathcal{L}_i^0(\mu, \theta_i) \times \prod_j^{M_i} \mathcal{A}(\theta_i^j)$
 - μ is parameter of interest
 - θ_i are the set of nuisance parameters used in channel i
 - \mathcal{L}_i^0 is the main body of the likelihood (eg observable distribution)
 - $\mathcal{A}(\theta_i^j)$ are auxiliary constraints for each θ_i^j (eg unit gaussian)

- Build a combined likelihood $\mathcal{L}(\mu, \theta) = \left(\prod_i^N \mathcal{L}_i^0(\mu, \theta_i) \right) \times \left(\prod_j^M \mathcal{A}(\theta^j) \right)$
 - θ is now the set of all *unique* nuisance parameters
 - **Some θ_i^j are shared between channels.** This must be recognized to ensure proper correlation.

Combination Details

- At first (one or two combinations), ATLAS results were fully based on toys
- As model grew, these became impractical
 - ~ 570 nuisance parameters at time of discovery
 - ~ 310 of these are due to MC stats, treated Barlow-Beeston style
- ~ 10 -30 minutes per fit \rightarrow 20-60 minutes per toy
 - $\mathcal{O}(\text{millions})$ CPU hours to produce full result
- Large model gives many fit failures, leads to false toys in tails of distribution
 - Diagnostic tools used to ensure tail events were truly failures
 - p-values become falsely enhanced, gives conservative result
- This led us to use asymptotics for all results, validated with toy and Bayesian tests

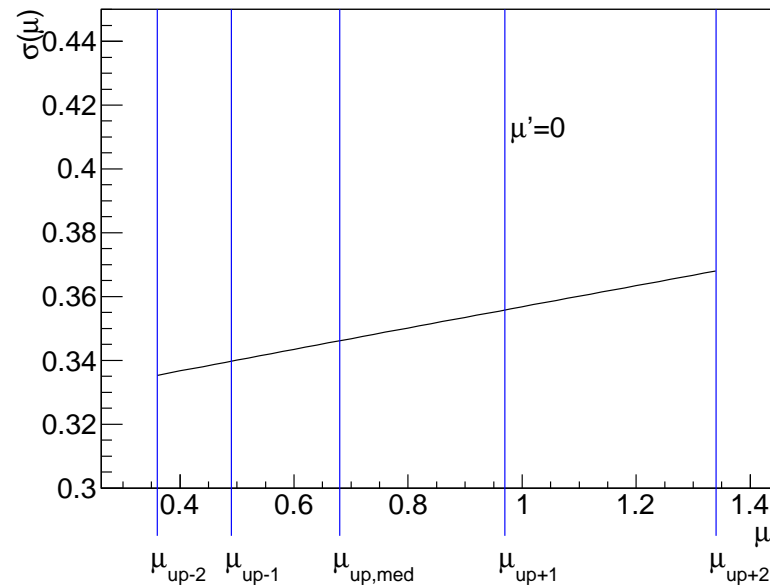


Asymptotic Bands

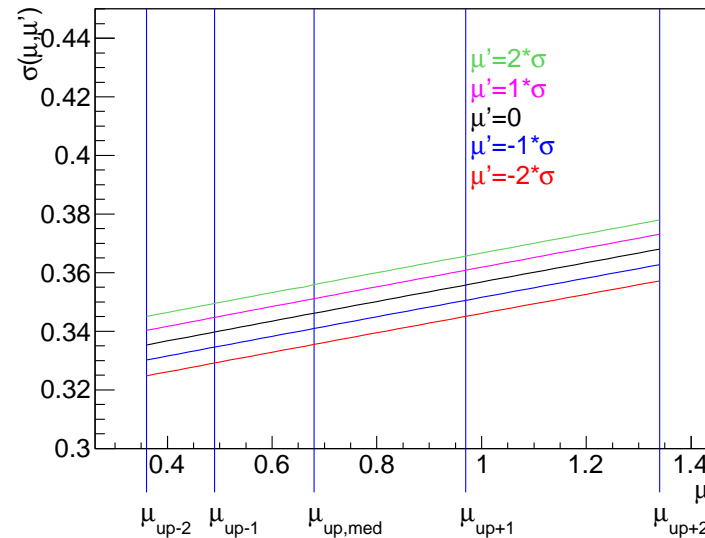
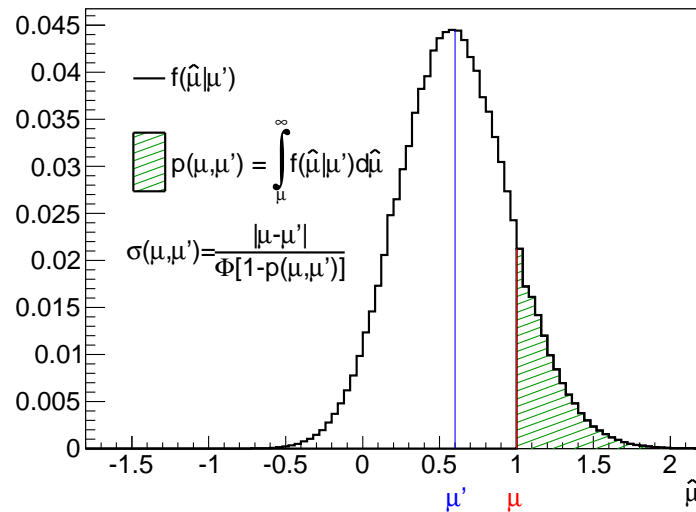
Asymptotic Limit Bands

- When σ is μ -dependent, simple equation for limit bands fails

$$\begin{aligned}
 \text{CLS}(\mu_{\text{up}+N}) &\equiv \alpha && \approx (1 - \Phi(\frac{\mu_{\text{up}+N} - N\sigma_1}{\sigma_2})) / (\Phi(\frac{\mu_{\text{up}+N}}{\sigma_3} - \frac{\mu_{\text{up}+N} - N\sigma_1}{\sigma_2})) \\
 &&& \neq (1 - \Phi(\frac{\mu_{\text{up}+N} - N\sigma_1}{\sigma_2})) / (\Phi(N)) \\
 \Rightarrow \mu_{\text{up}+N} &\neq \sigma \{ \Phi^{-1}[1 - \alpha\Phi(N)] + N \}
 \end{aligned} \tag{1}$$

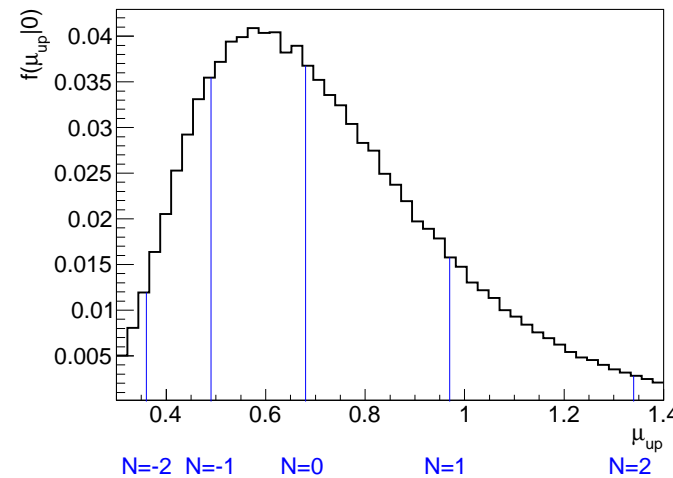
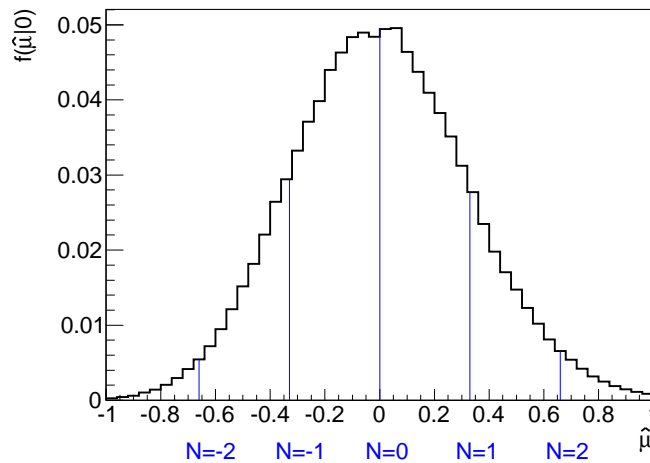


Estimating σ



- $\sigma \approx \frac{|\mu - \mu'|}{\sqrt{t_{\mu, A_{\mu'}}}}$ really involves two μ 's: μ and μ'
- To conceptualize, imagine the toy distribution $f(\hat{\mu}|\mu')$ from which σ can be extracted
 - μ' is the hypothesized value \sim median of the distribution
 - μ is the tested value from which you integrate to extract σ

Mapping



- In result using toys, μ_{up} is found for each b-only toy by scanning test statistic until it crosses some calibrated threshold
 - Band is derived from the quantiles of the distribution of μ_{up}
- If asymptotic properties hold, there should be a one-to-one mapping between the quantiles of $f(\hat{\mu}|0)$ and $f(\mu_{up}|0)$
 - The N 'th quantile of $f(\hat{\mu}|0)$, call it μ'_N , therefore characterizes the Asimov dataset for the N 'th quantile expected limit

Using the N'th Quantile Asimov

- Construct five Asimov datasets, one for each $N=-2, \dots, 2$
 - μ'_N found by scanning $\mu' = 0$ Asimov NLL to find $-2 \log \lambda(\mu'_N) = N^2$
 - Nuisance parameters $\hat{\theta}(\mu'_N)$ also taken from $\mu' = 0$ Asimov fit when constructing μ'_N Asimov dataset
 - These Asimov datasets characterize quantiles of $f(\hat{\mu}|0)$ that we wish to map to $f(\mu_{up+N}|0)$
- Use each Asimov dataset to find the crossing $CLs(\mu_{up+N}) = \alpha$
 - Implicit in the $CLs(\mu_{up+N}) = \alpha$ is the mapping function to go from $f(\hat{\mu}|0)$ to $f(\mu_{up}|0)$



Comparison

Comparison of expected upper limit band						
	Low systematics			High systematics		
Quantile	Old μ_{up}	Improved μ_{up}	Toy μ_{up}	Old μ_{up}	New μ_{up}	Toy μ_{up}
+2	1.27	1.34	1.32	1.27	2.78	2.82
+1	0.95	0.97	0.96	0.94	1.25	1.25
0	0.68	0.68	0.68	0.68	0.68	0.68
-1	0.49	0.48	0.48	0.49	0.42	0.42
-2	0.37	0.36	0.36	0.36	0.29	0.28

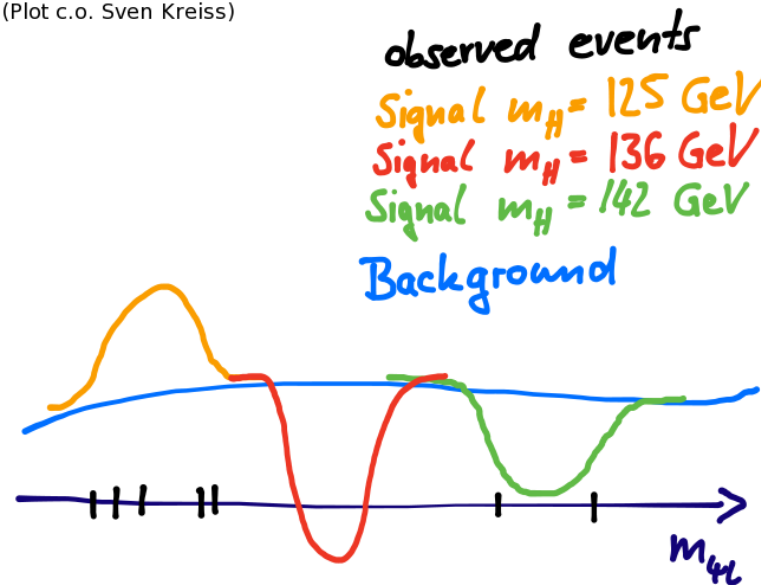
- New procedure reproduces toy results well
- Differences are especially striking when systematics are large
 - μ -dependence of σ is large in these cases, which is exactly the scenario the new method was designed to address



Low count $\hat{\mu}$ / Physical PDF

Low count $\hat{\mu}$ / Physical PDF

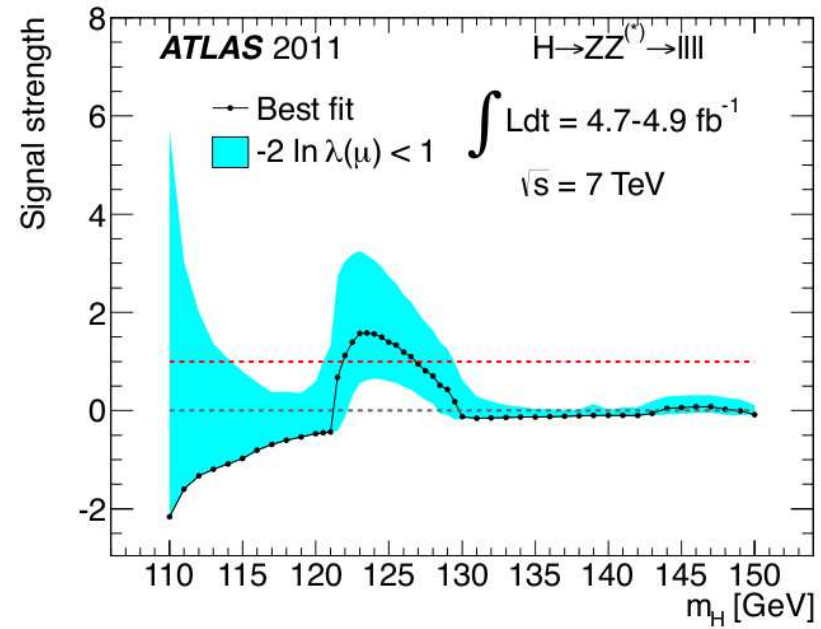
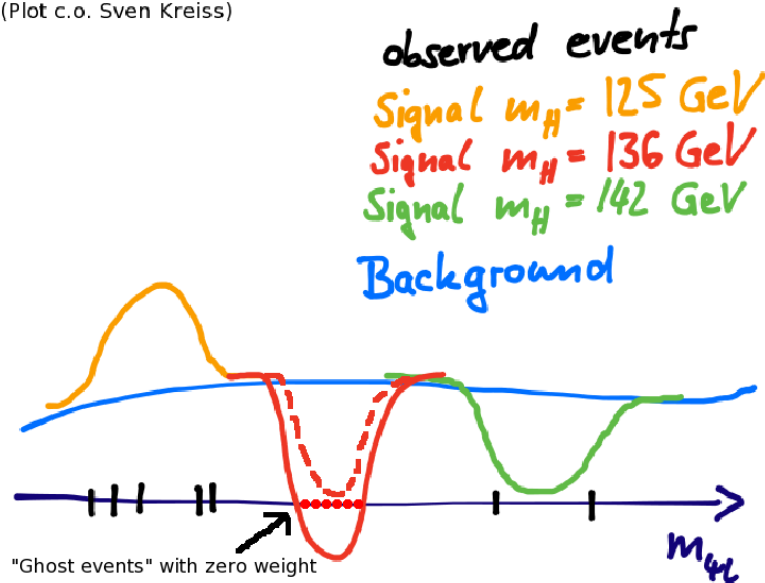
(Plot c.o. Sven Kreiss)



- In resonance models with low event counts like $H \rightarrow ZZ^{(*)} \rightarrow llll$, PDF can become negative when fitting signal with no observed events
- Issue is mostly technical
 - Likelihood only evaluated on data points
 - Difficult to check PDF is physical everywhere in a general way

Low count $\hat{\mu}$ / Physical PDF

(Plot c.o. Sven Kreiss)



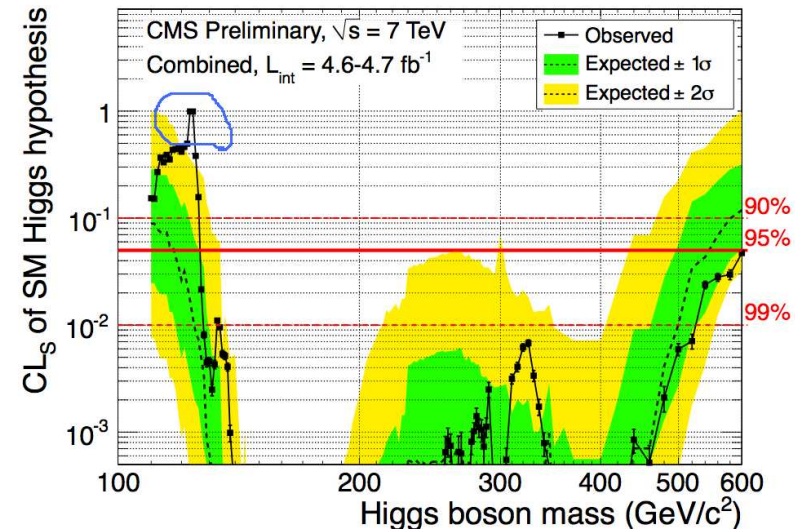
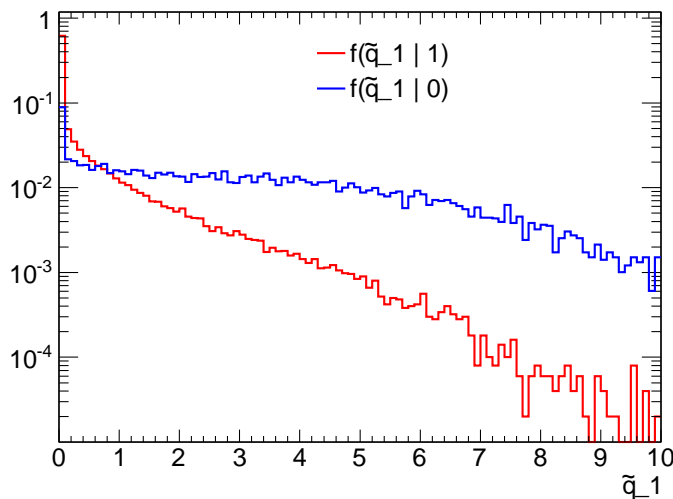
- "Ghost events" with zero weight can be added around signal peak to force RooFit to check if PDF is negative
- This causes the familiar wall in the $\hat{\mu}$ plot on the right

$$- \hat{\mu}_{\min} \approx - \frac{B(x_{\text{peak}})}{S(x_{\text{peak}})}$$



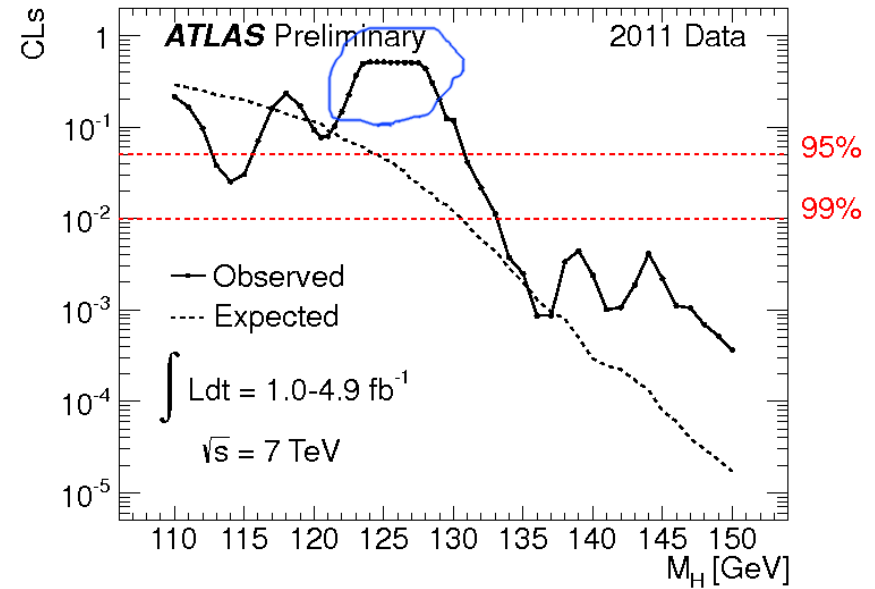
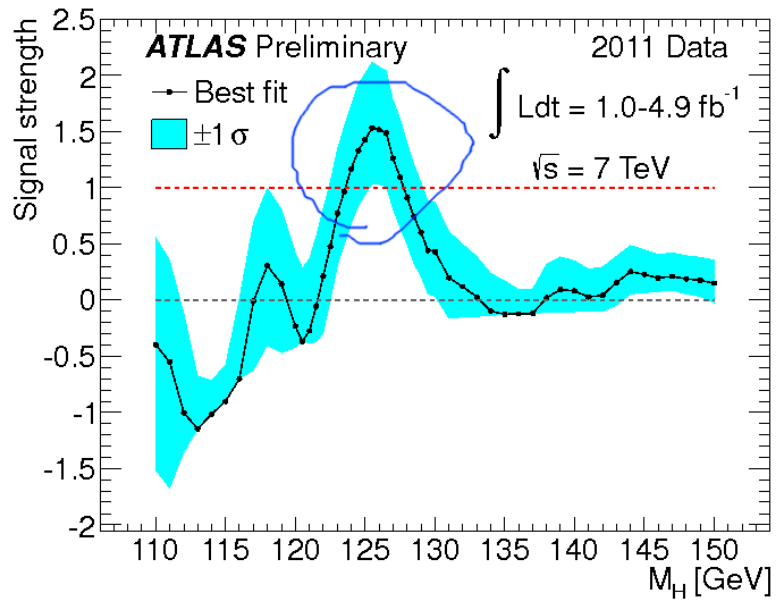
P-Value Uncapping

P-Value Uncapping

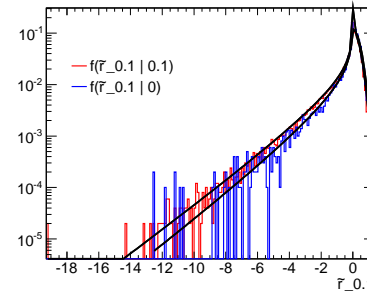
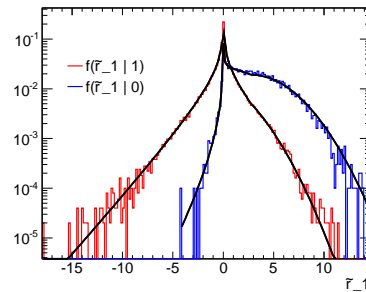


- Classically, $CL_s \rightarrow 1$ continuously as $Q \rightarrow -\infty$
- Condition $\tilde{q}_\mu = 0$ for $\hat{\mu} > \mu$ leads to $\delta(\tilde{q}_\mu)$ in $f(\tilde{q}_\mu | \mu')$ that breaks this
 - Similar issue for q_0 when $\hat{\mu} < 0$
- \tilde{q}_μ, q_0 can be redefined to reveal structure of excesses and deficits

Example



Redefining \tilde{q}_μ



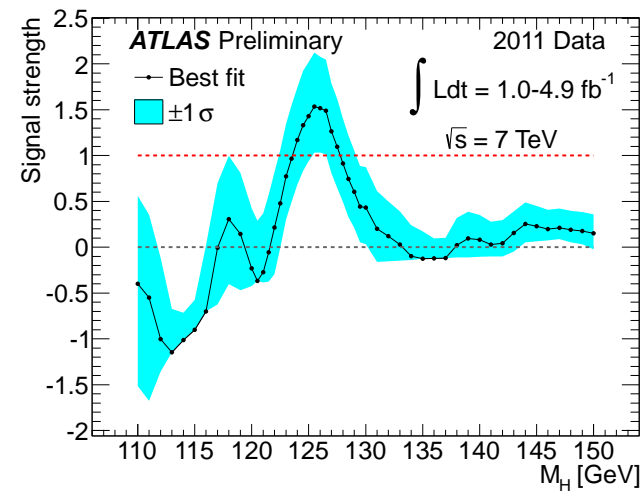
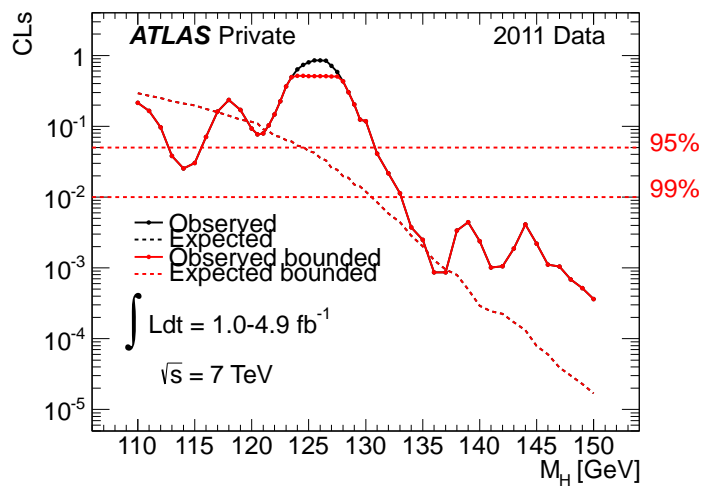
- We can gain back information lost in $\delta(\tilde{q}_\mu)$ by defining a new test stat \tilde{r}_μ

$$\tilde{r}_\mu = \begin{cases} +(-2 \ln \lambda(0)) & \hat{\mu} \leq 0 & (same) \\ +(-2 \ln \lambda(\mu)) & 0 < \hat{\mu} < \mu & (same) \\ -(-2 \ln \lambda(\mu)) & \hat{\mu} \geq \mu & (new!) \end{cases}$$

$$F(\tilde{r}_\mu | \mu') = \begin{cases} \Phi\left(\frac{\tilde{r}_\mu - (\mu^2 - 2\mu\mu')}{2\mu/\sigma}\right) & \frac{\mu^2}{\sigma^2} \leq \tilde{r}_\mu & (same) \\ \Phi\left(\sqrt{\tilde{r}_\mu} + \frac{\mu - \mu'}{\sigma}\right) & 0 < \tilde{r}_\mu < \frac{\mu^2}{\sigma^2} & (same) \\ \Phi\left(-\sqrt{-\tilde{r}_\mu} + \frac{\mu - \mu'}{\sigma}\right) & \tilde{r}_\mu \leq 0 & (new!) \end{cases}$$

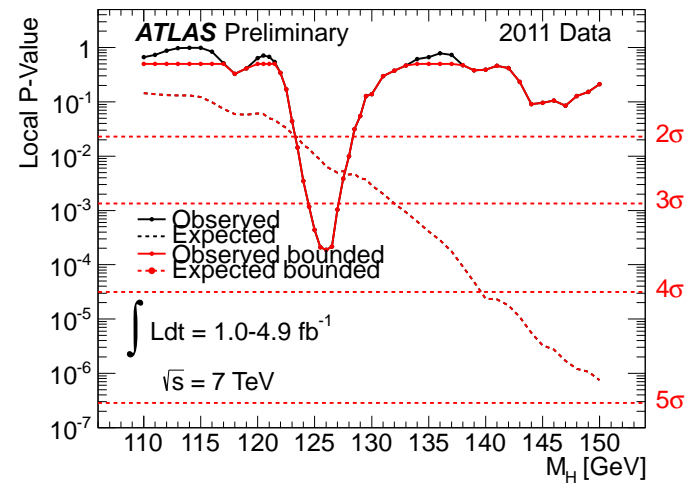
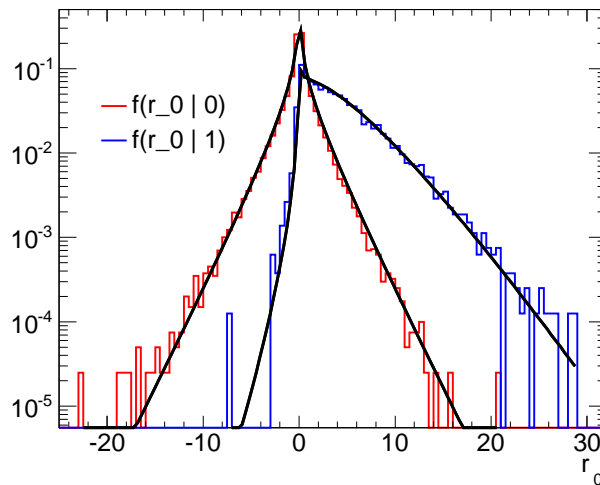
- Identical for expected p-values and observed cases of $\hat{\mu} < \mu$

Comparison



- As expected, behavior is identical for $\hat{\mu} < 1$
- For $\hat{\mu} > 1$, the new CDF kicks in and the CLs=0.5 cap is broken

Redefining q_0



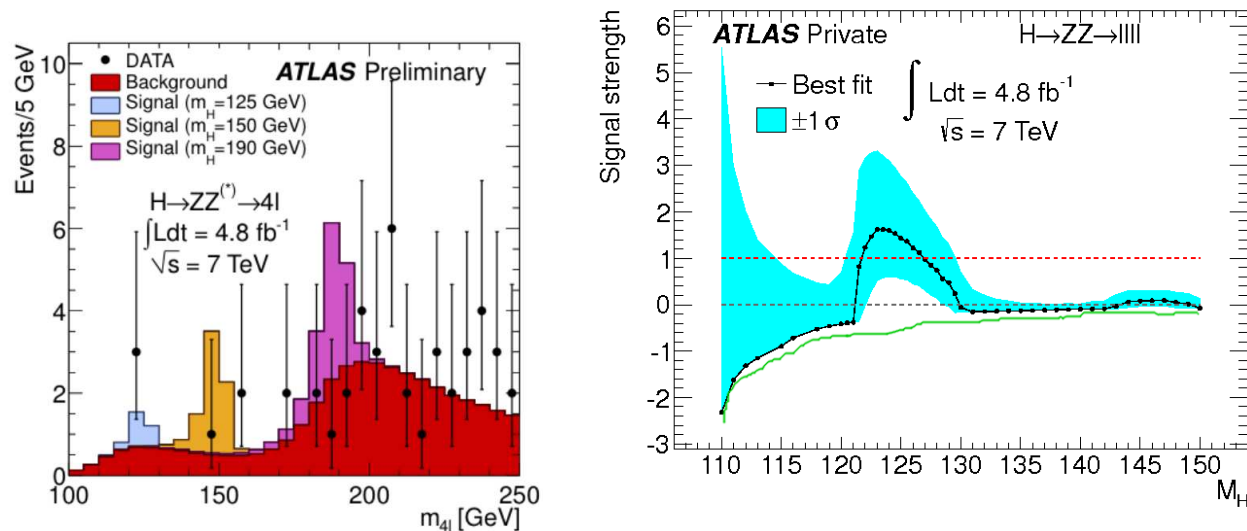
- r_0 can be defined similar to \tilde{r}_μ

$$r_0 = \begin{cases} +(-2 \ln \lambda(\mu)) & \hat{\mu} > 0 \quad (\text{same}) \\ -(-2 \ln \lambda(\mu)) & \hat{\mu} \leq 0 \quad (\text{new!}) \end{cases}$$

$$F(r_0 | \mu') = \begin{cases} \Phi(\sqrt{r_0} - \frac{\mu'}{\sigma}) & r_0 > 0 \quad (\text{same}) \\ \Phi(-\sqrt{-r_0} - \frac{\mu'}{\sigma}) & r_0 \leq 0 \quad (\text{new!}) \end{cases}$$

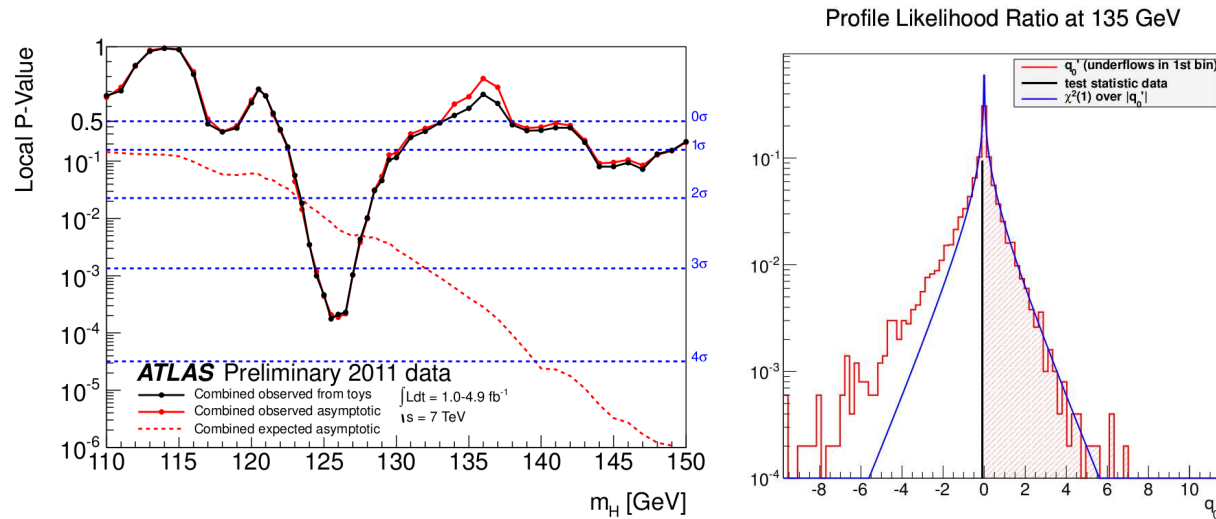
- Identical for expected p-values and observed cases of $\hat{\mu} > 0$

Physical PDF issues



- Ghost events come back to haunt us!
- To deal with the physical PDF issue, ghost events would have to be added to each toy in the ensemble
 - This will break the asymptoticity of r_0 toys if not dealt with

Practical example



- p_0 with toys for ATLAS combination courtesy of Tim Adye
 - Negative r_0 toy distribution deviates from asymptotics
 - $\hat{\mu}$ goes more negative than it should, leading to larger r_0 values
- Physical pdf isn't explicitly required within RooFit toys
- NB: Asymptotics can be taught about physical pdf
 - Difficult to do in a model independent way for toys



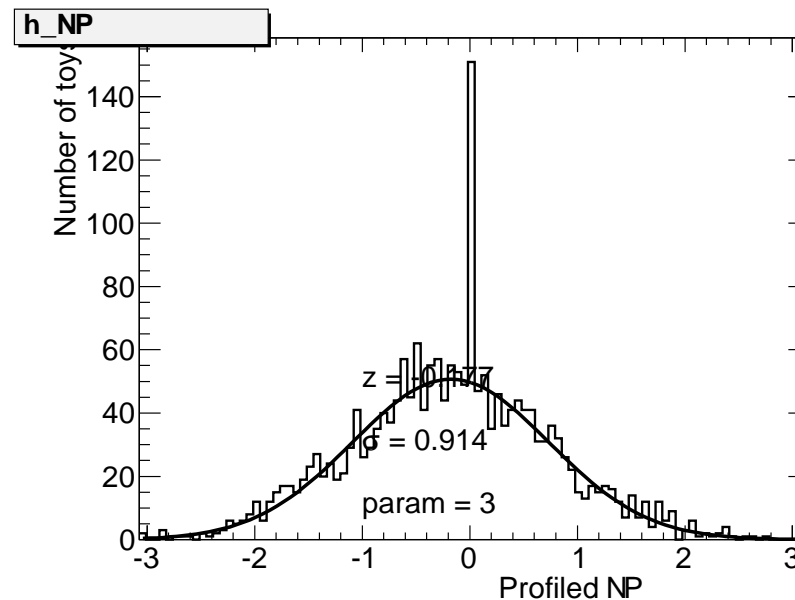
Asymmetric Uncertainties / NP Distributions

Asymmetric Uncertainties

- Systematics are treated as lognormally distributed
 - For a normally distributed nuisance parameter θ , $\nu(\theta) \equiv \kappa^\theta$ is lognormally distributed
 - $\nu(\theta)$ multiplies our expected rates: $B(\theta) = B_0\nu(\theta)$
- κ determined by calculating $\nu(\theta)$ at $\theta = \pm 1$
 - Eg, vary JES by $\pm 1\sigma$ and look at effect on background
 - Leads to two values of κ : $\kappa_\pm = \nu(\pm 1)$
 - If $\kappa_+ \neq \kappa_-$, uncertainty is asymmetric
- Asymmetric uncertainties were at first handled by bifurcating $\nu(\theta)$

$$\nu(\theta) = \begin{cases} \kappa_+^\theta, & \theta \geq 0 \\ \kappa_-^\theta, & \theta < 0 \end{cases} \quad (2)$$

Asymmetric Uncertainties



- Look at posterior distribution of maximum likelihood estimators $\hat{\theta}$
- Bifurcation leads to unphysical delta function in distribution
 - This causes kink in likelihood vs θ and a discontinuous first derivative
 - Instabilities in Minuit cause delta at $\theta = 0$

Response Function Interpolation

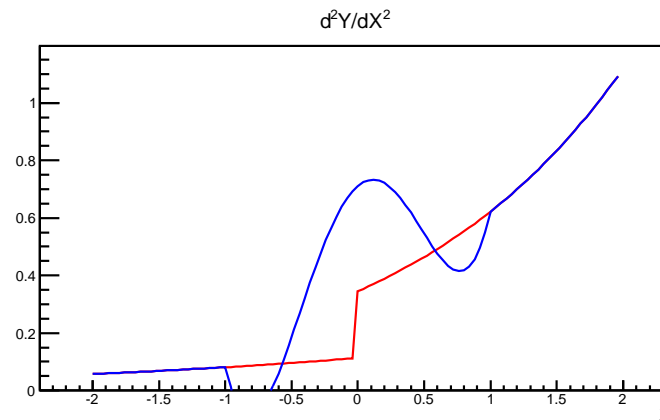
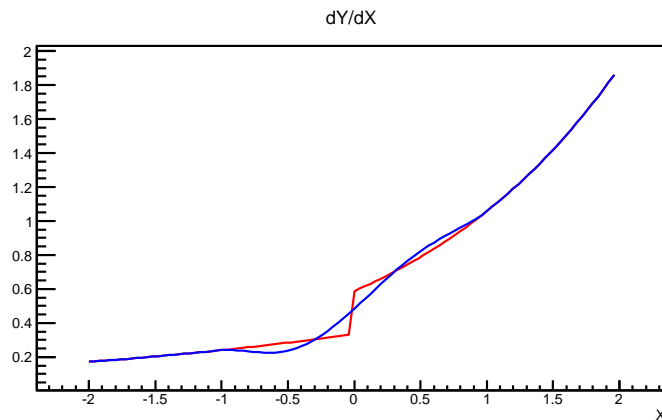
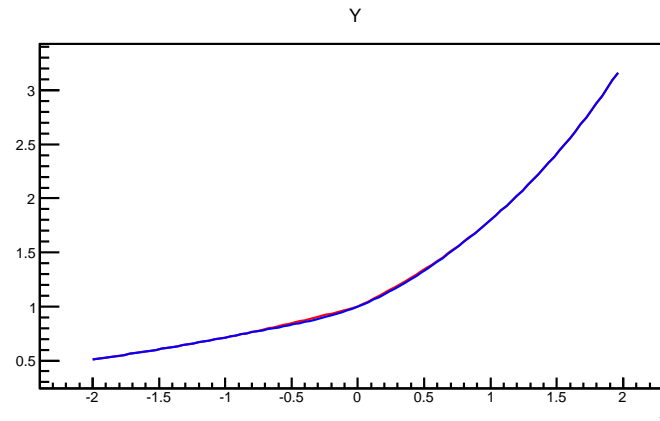
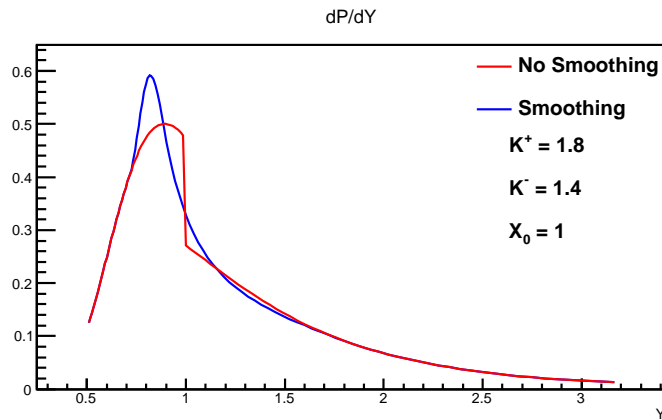
- Introduce a polynomial function in the transition region
 - A 6D polynomial is required to satisfy $\nu, \frac{d\nu}{d\theta}, \frac{d^2\nu}{d\sigma^2}$ continuity
- Embed the transition function in some range $(-X_0, +X_0)$ (nominally $(-1,1)$)

$$\nu(\theta) = \begin{cases} \kappa_+^\theta, & \theta \geq X_0 \\ 1 + \sum_{i=1}^6 a_i \theta^i, & -X_0 < \theta < X_0 \\ \kappa_-^\theta, & X \leq -X_0 \end{cases}$$

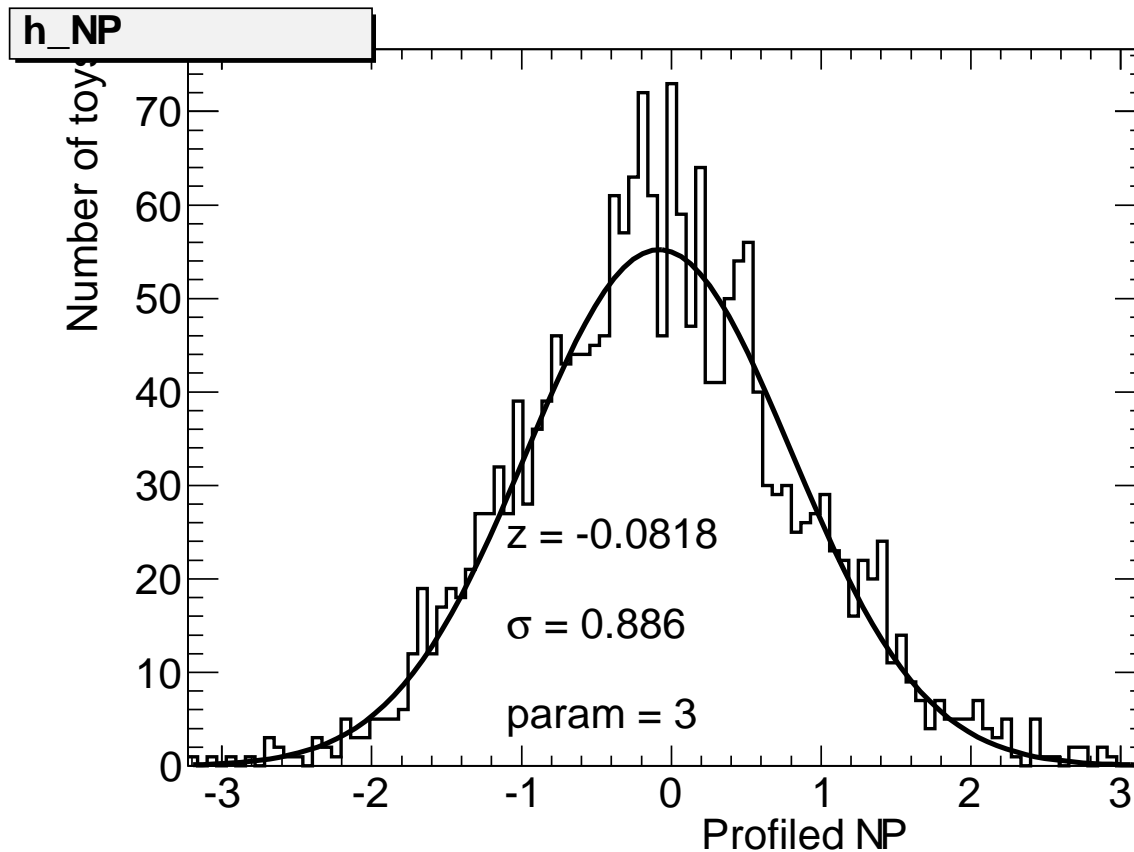
- a_i determined by requiring continuity up to the second derivative at the boundaries $-X_0, +X_0$



Response Function Comparison



Result



- Delta function is removed and θ returns to its proper gaussian distribution



Summary

- Several statistics and modelling issues addressed in last two years during Higgs search
 - These became apparent as model matured and as we learned to develop tools to understand our results
 - Typically developed out of necessity during conference rush
 - PDF physicality, asymmetric systematic handling
- Asymptotic methods have grown to better approximate toy results
 - Band formulation, uncapping