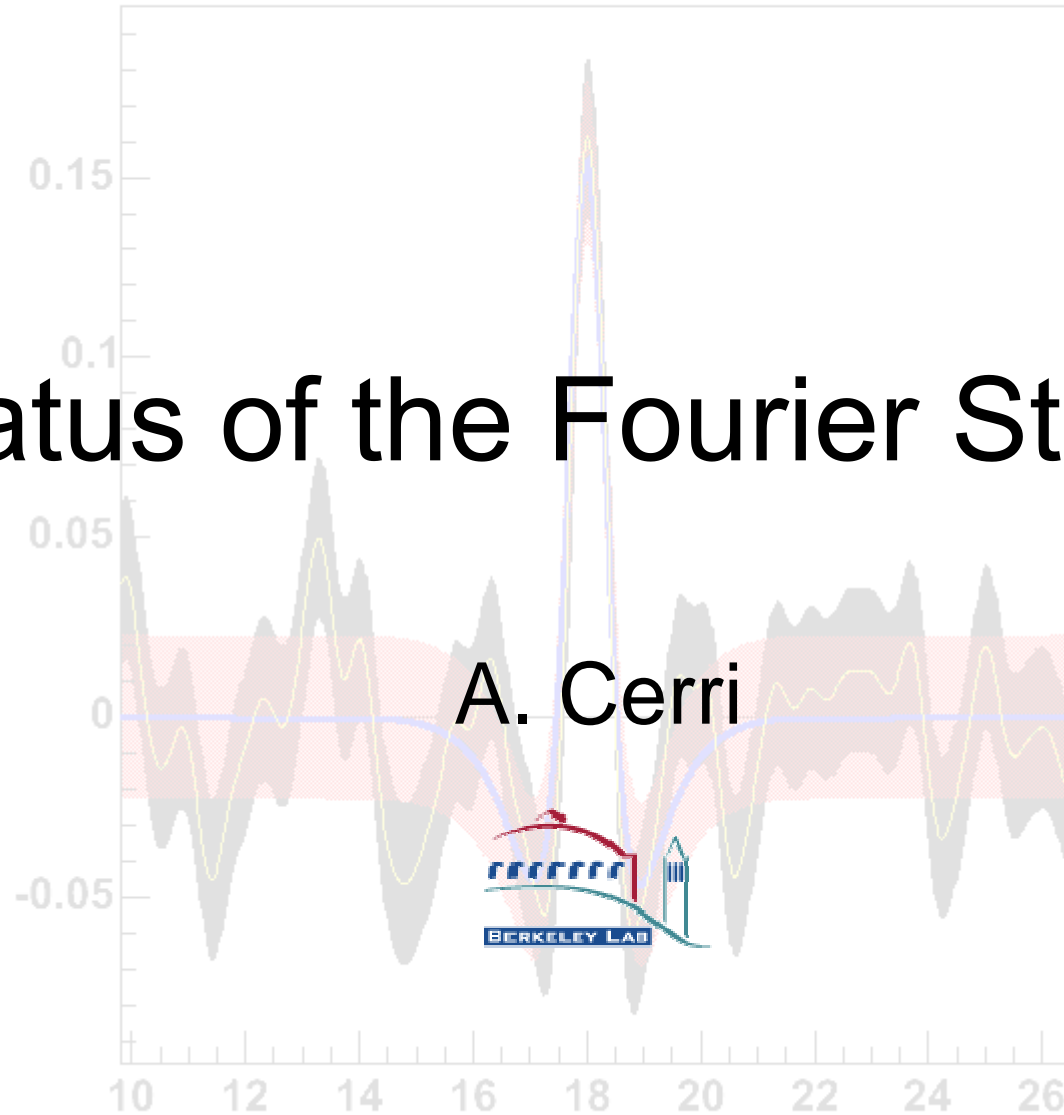


# Status of the Fourier Studies



A. Cerri



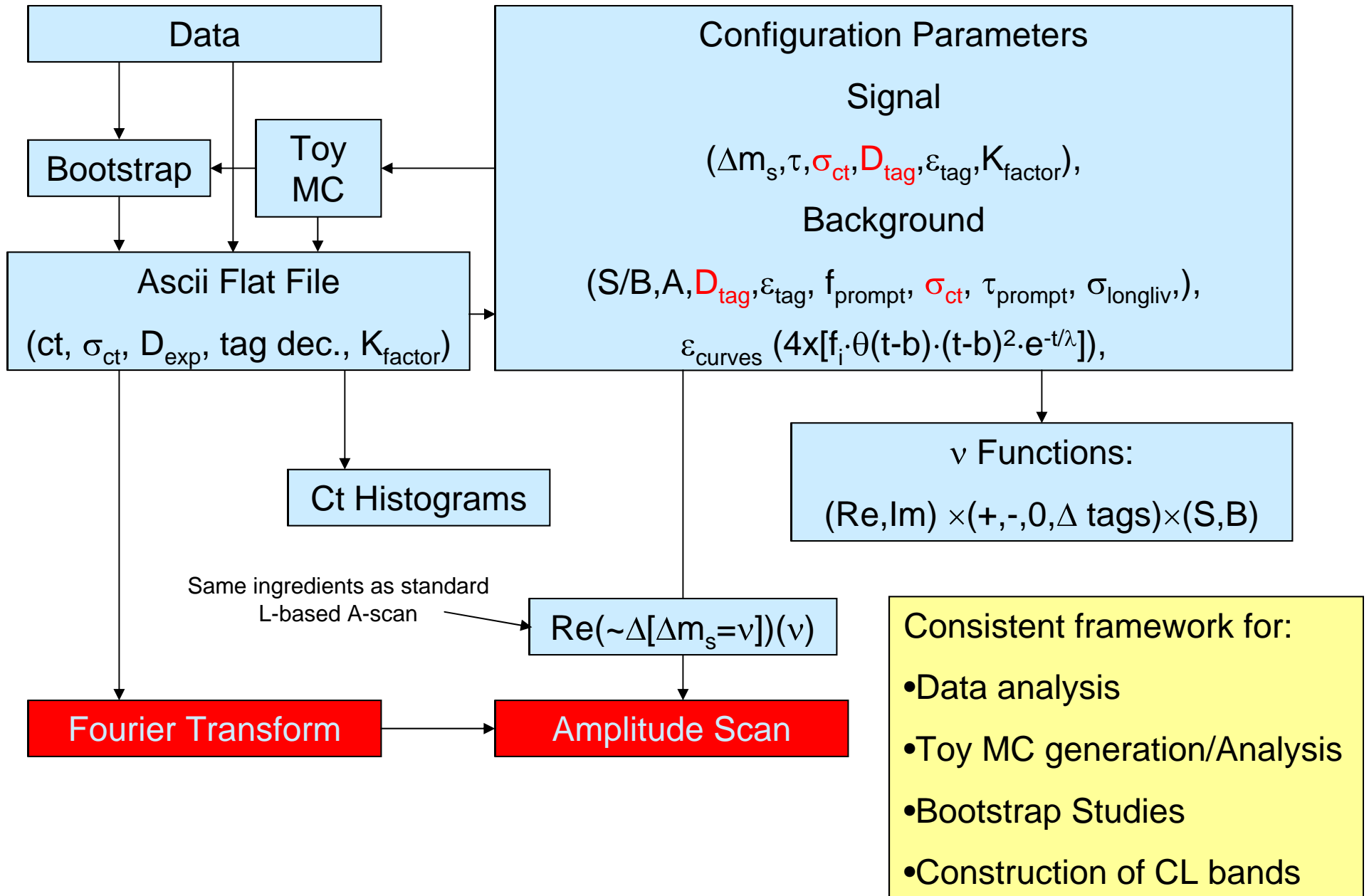
# Outline

- Introduction
- Description of the tool
- Validation
  - “lifetime fit”
  - Pulls
- Toy Montecarlo
  - Ingredients
  - Comparison with data
- Building Confidence Bands
- Measuring Peak Position
- Conclusions

# Introduction

- Principles of fourier based method presented on 12/6/2005, 12/16/2005, 1/31/2006, 3/21/2006
- Methods documented in CDF7962 & CDF8054
- Aims:
  - settle on a completely fourier-transform based procedure
  - Provide a tool for possible analyses, e.g.:
    - $J/\psi\phi$  direct CP terms
    - $D_s K$  direct CP terms
  - Compare as much as we can to the mixing results as a sanity check on the main mode ( $\phi\pi$ )
  - All you will see is restricted to  $\phi\pi$ . Focusing on this mode alone for the time being
- **Not our Aim:** bless a summer mixing result

# Tool Structure

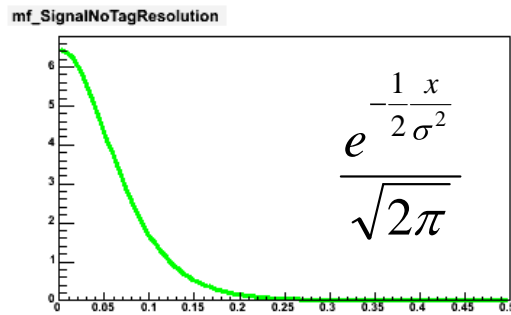


# Validation:

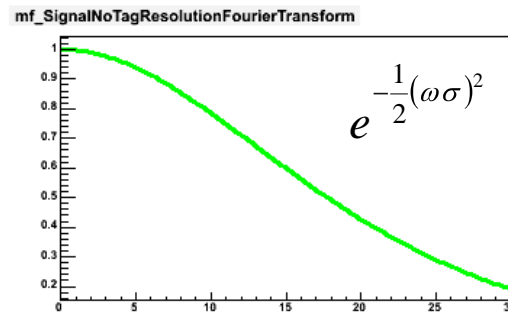
- Toy MC Models
- “Fitter” Response

# Ingredients in Fourier space

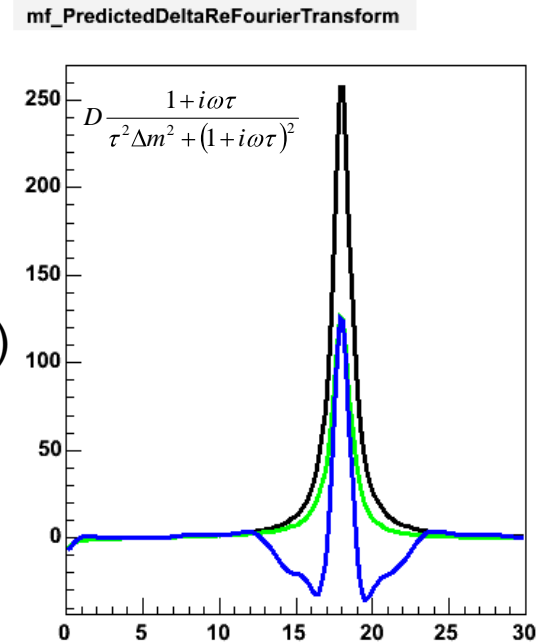
Resolution Curve (e.g. single gaussian)



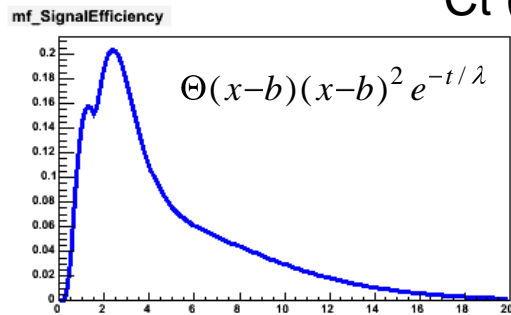
Ct (ps)



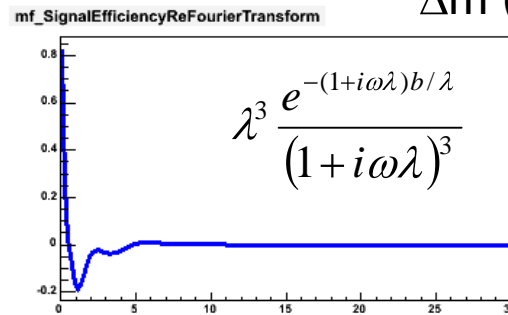
Δm (ps<sup>-1</sup>)



Δm (ps<sup>-1</sup>)



Ct (ps)



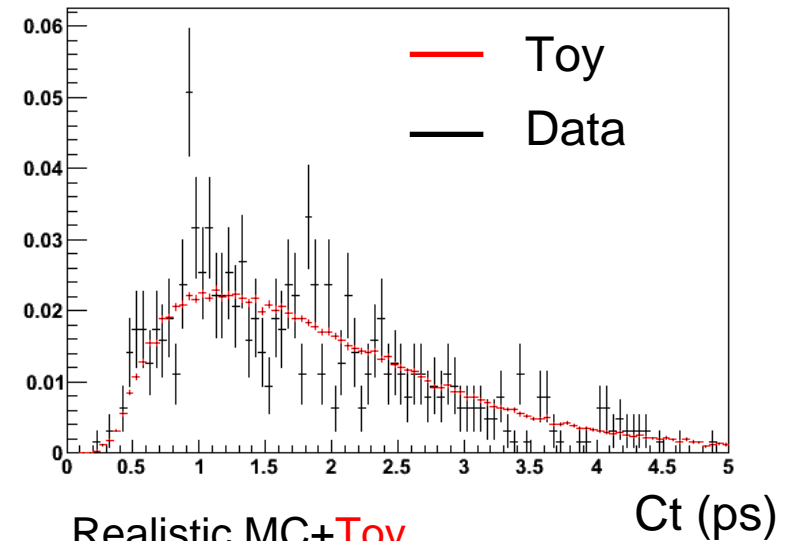
Δm (ps<sup>-1</sup>)

Ct efficiency curve, random example

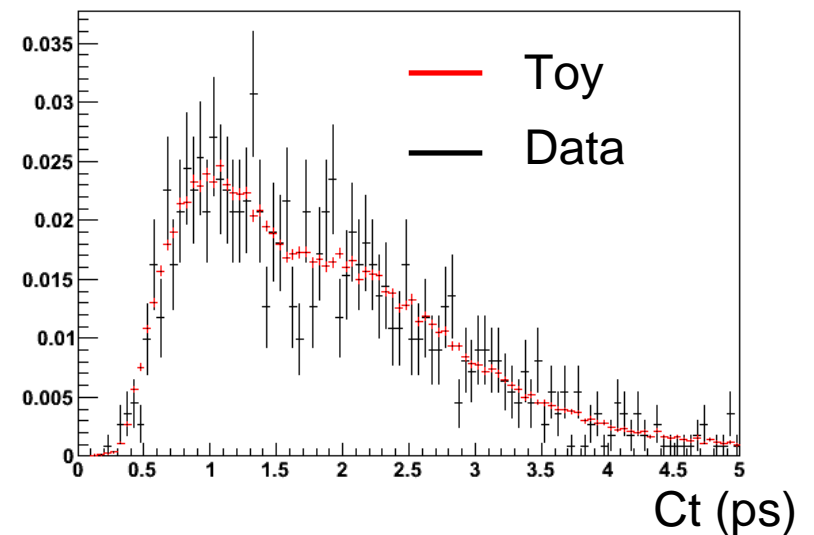
# Toy Montecarlo

- As realistic as it can get:
  - Use histogrammed  $\sigma_{ct}$ ,  $D_{tag}$ ,  $K_{factor}$
  - Fully parameterized  $\varepsilon_{curves}$
  - **Signal:**
    - $\Delta m$ ,  $\Gamma$ ,  $\Delta\Gamma$
  - **Background:**
    - Prompt+long-lived
    - Separate resolutions
    - Independent  $\varepsilon_{curves}$

Data+Toy

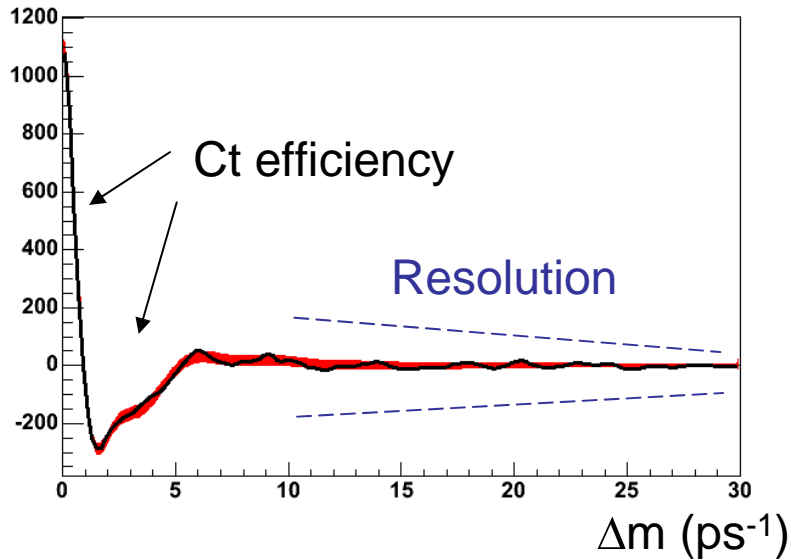


Realistic MC+Toy



# Flavor-neutral checks

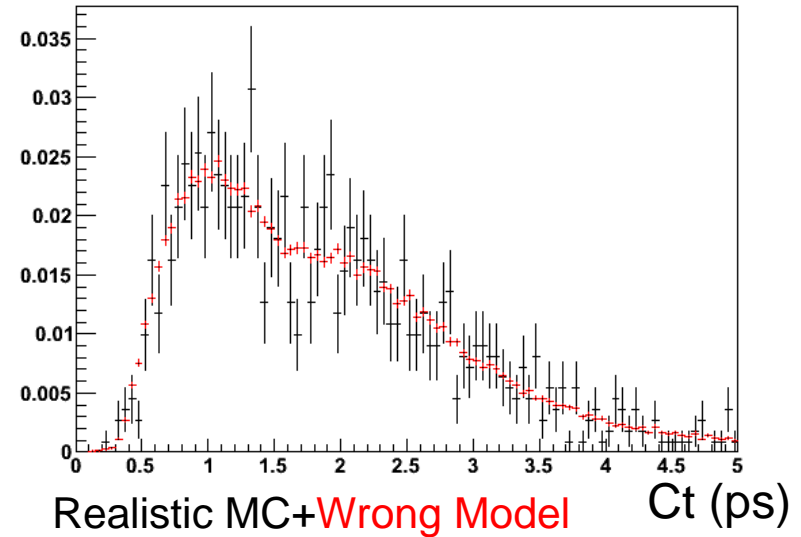
Realistic MC+Model



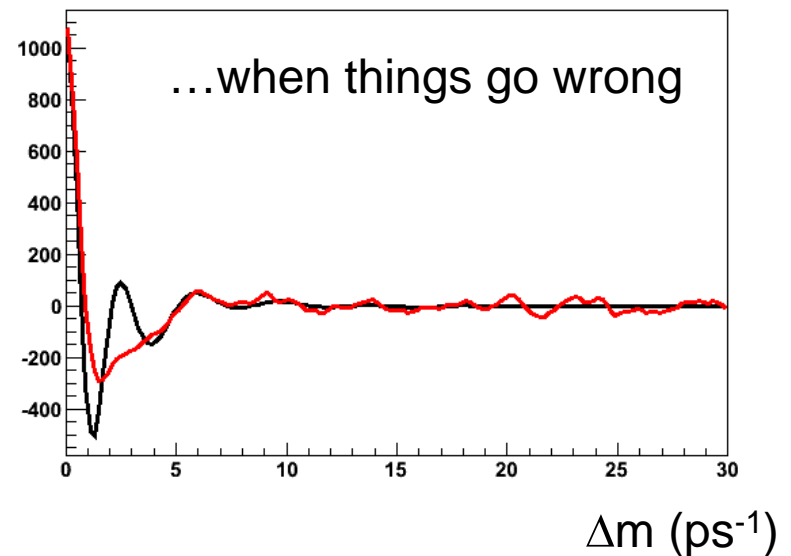
Re(+)+Re(-)+Re(0) Analogous to a lifetime fit:

- Unbiased WRT mixing
- Sensitive to:
  - Eff. Curve
  - Resolution

Realistic MC+Toy



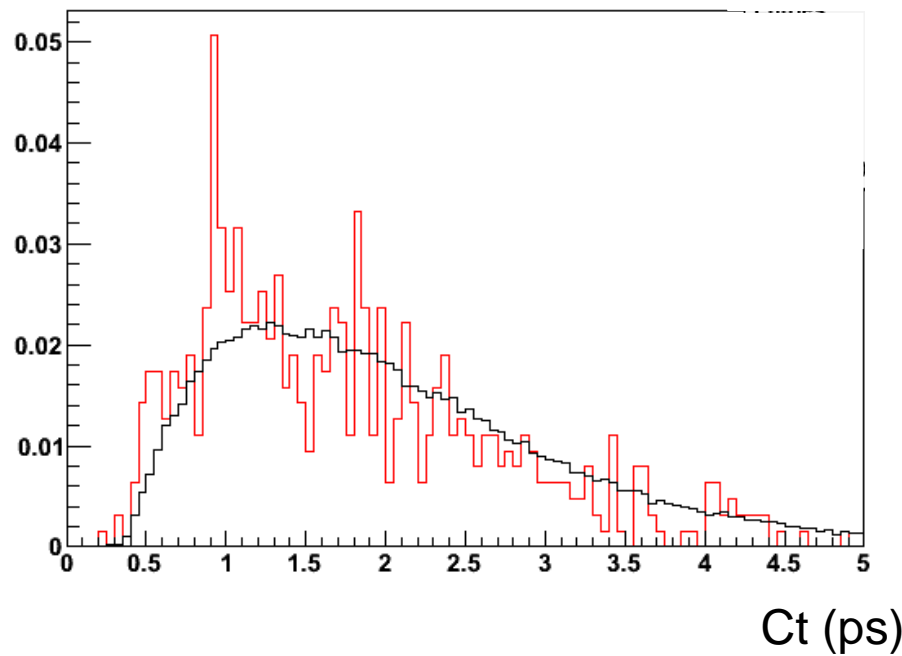
Realistic MC+Wrong Model



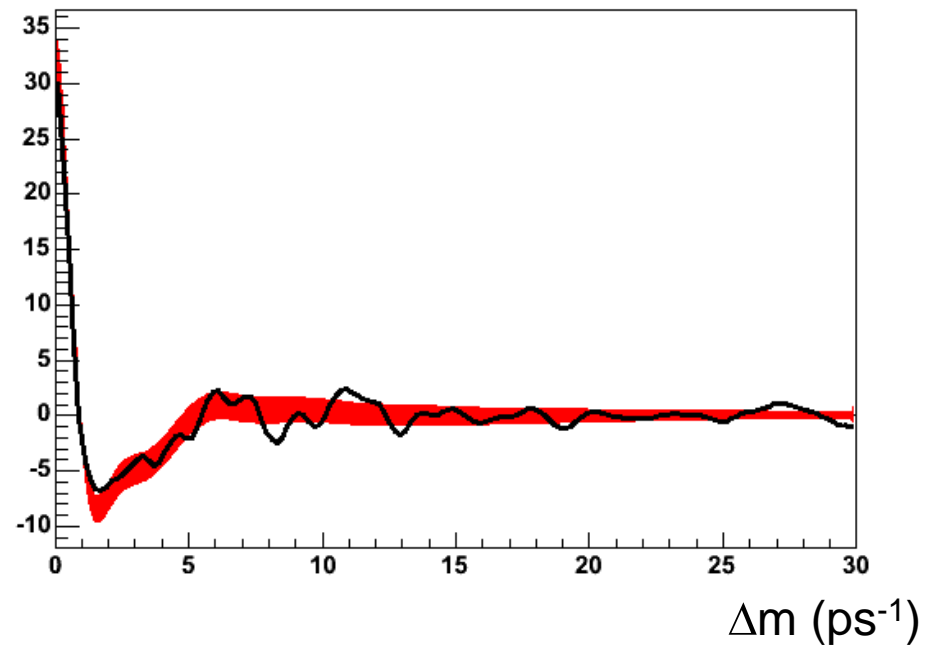


# “Lifetime Fit” on Data

Data vs **Toy**



Data vs **Prediction**



Comparison in  $ct$  and  $\Delta m$  spaces of data and toy MC distributions

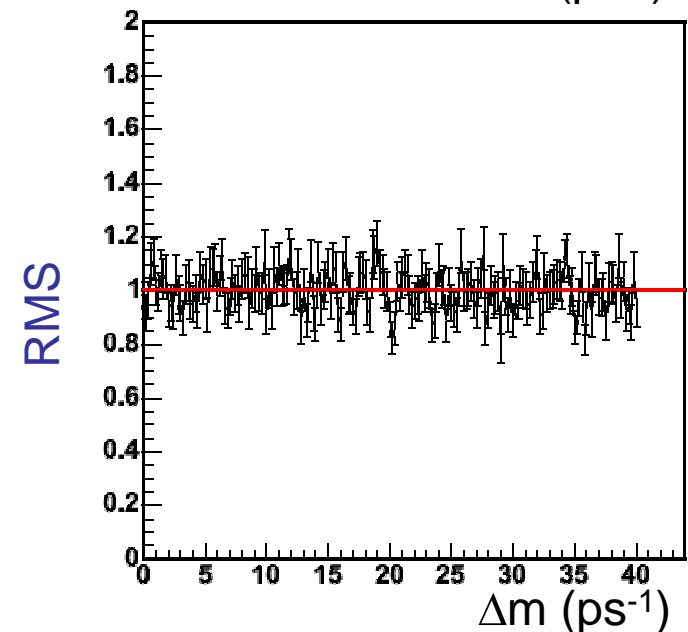
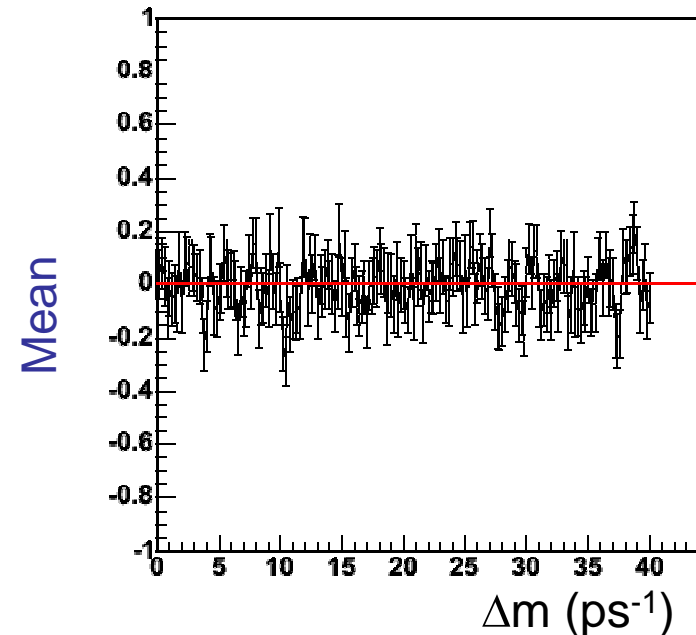
# “Fitter” Validation

“pulls”

$Re(x)$  or  $\Delta=Re(+)-Re(-)$  predicted (value,  $\sigma$ ) vs simulated.

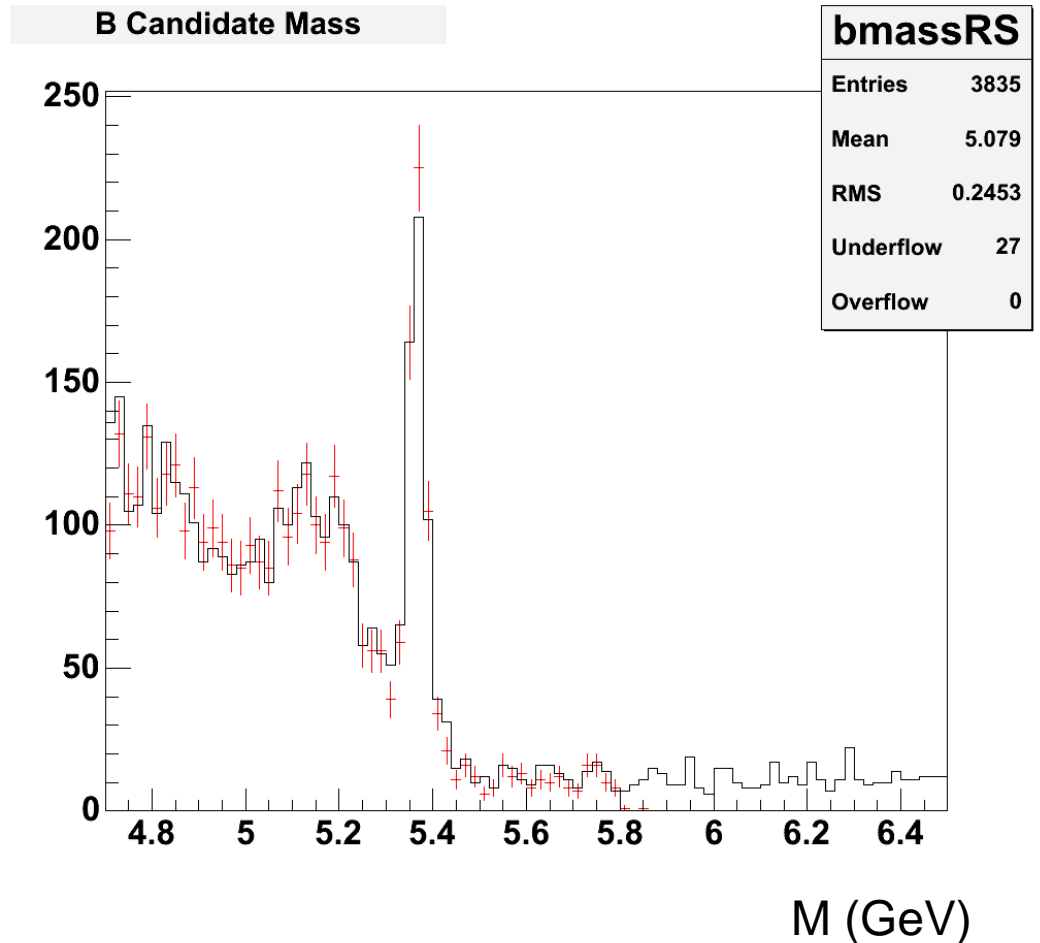
Analogous to Likelihood based fit pulls

- Checks:
  - Fitter response
  - Toy MC
- Pull width/RMS vs  $\Delta m_s$  shows perfect agreement
- Toy MC and Analytical models **perfectly consistent**
- Same reliability and consistency you get for L-based fits



# Unblinded Data

- Cross-check against available blessed results
- No bias since it's all unblinded already
- Using OSTags only
- **Red**: our sample, blessed selection
- **Black**: blessed event list
- This serves mostly as a proof of principle to show the status of this tool!

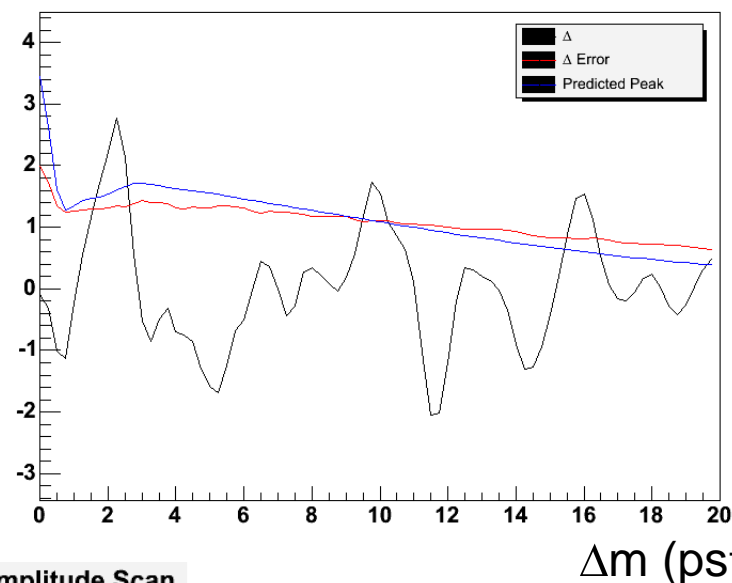


Next plots are based on data skimmed, using the OST only in the winter blessing style. No box has been open.

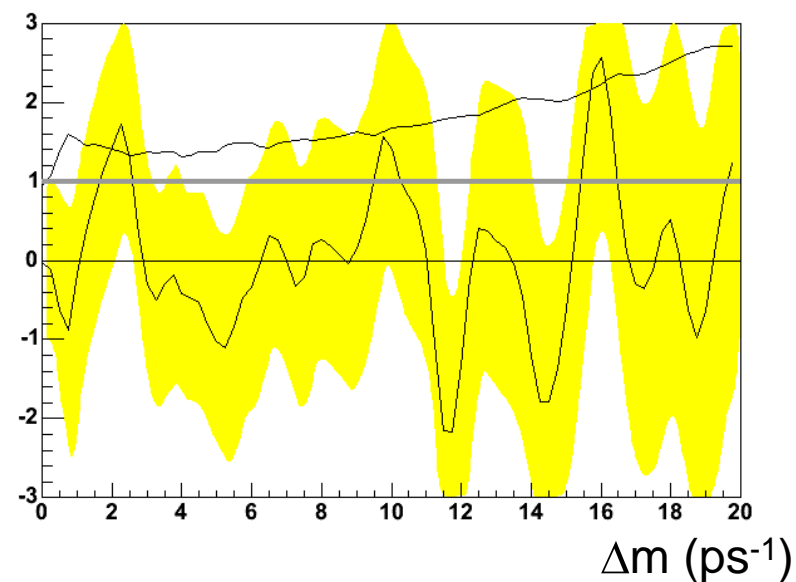
# From Fourier to Amplitude

- Recipe is straightforward:
  - 1) Compute  $\Delta(\text{freq})$
  - 2) Compute expected  $N(\text{freq}) = \Delta(\text{freq} \mid \Delta m = \text{freq})$
  - 3) Obtain  $A = \Delta(\text{freq}) / N(\text{freq})$
- No more data driven [ $N(\text{freq})$ ]
- Uses all ingredients of A-scan
- Still no minimization involved though!
- Here looking at  $Ds(\phi\pi)\pi$  only (350 pb<sup>-1</sup>, ~500 evts)
- Compatible with blessed results

Fourier Transform+Error+Normalization



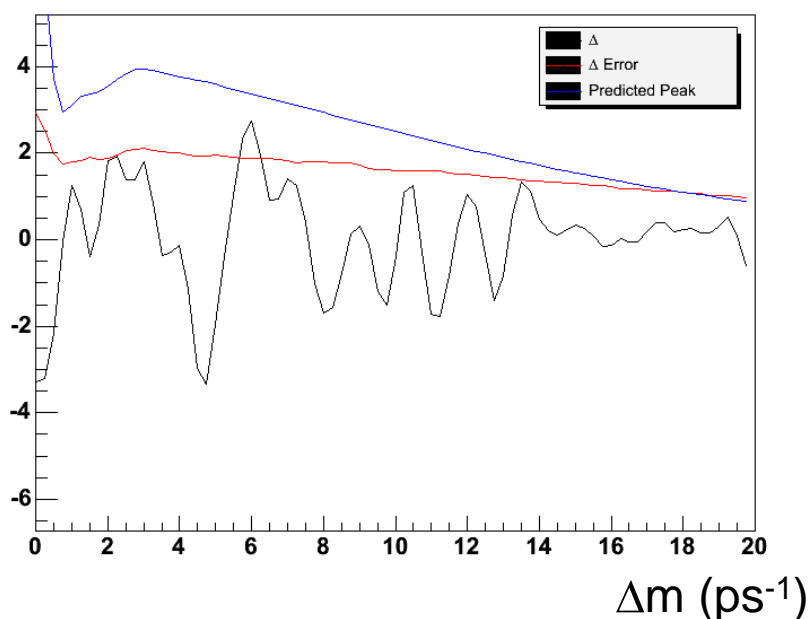
Amplitude Scan



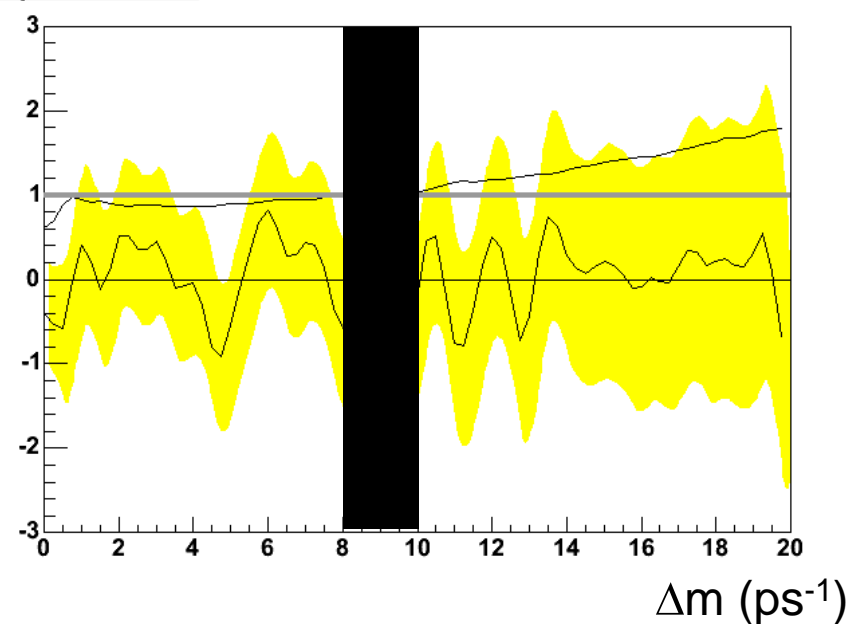
# Toy MC

- Same configuration as  $D_s(\phi\pi)\pi$  but  $\sim 1000$  events
- Realistic toy of sensitivity at higher effective statistics (more modes/taggers)

Fourier Transform+Error+Normalization



Amplitude Scan



Able to run on data (ascii file) and even generate toy MC off of it

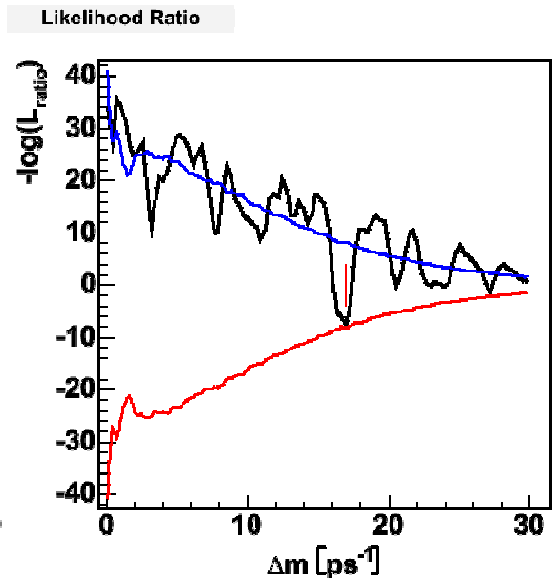
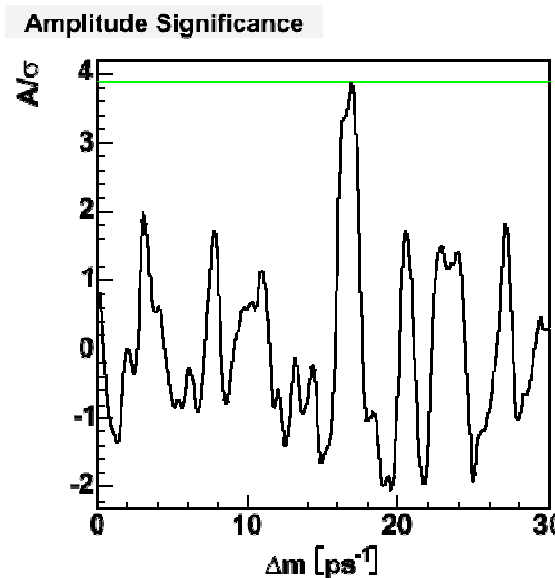
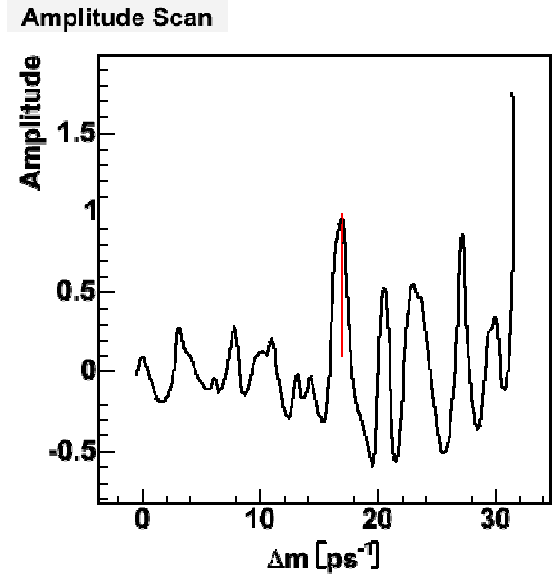
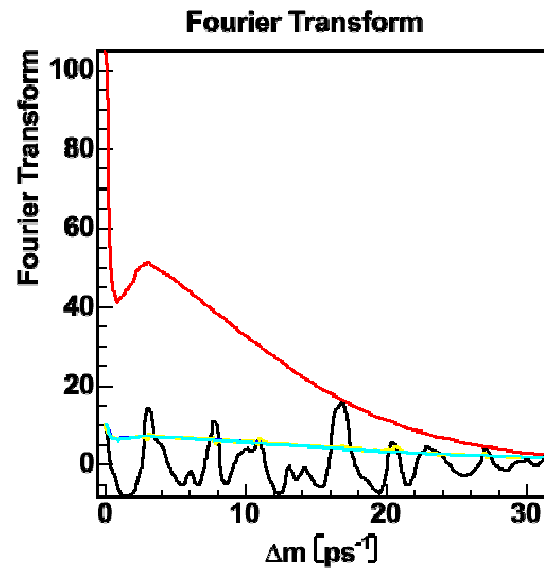
# Confidence Bands

# Peak Search

Minuit-based search of maxima/minima in the chosen parameter vs  $\Delta m$

Two approaches:

- Mostly Data driven:  
use  $A/\sigma$ 
  - Less systematic prone
  - Less sensitive
- Use the full information (L ratio):
  - More information needed
  - Better sensitivity  
(REM here sensitivity is defined as 'discovery potential' rather than the formal sensitivity defined in the mixing context)
- We will follow both approaches in parallel



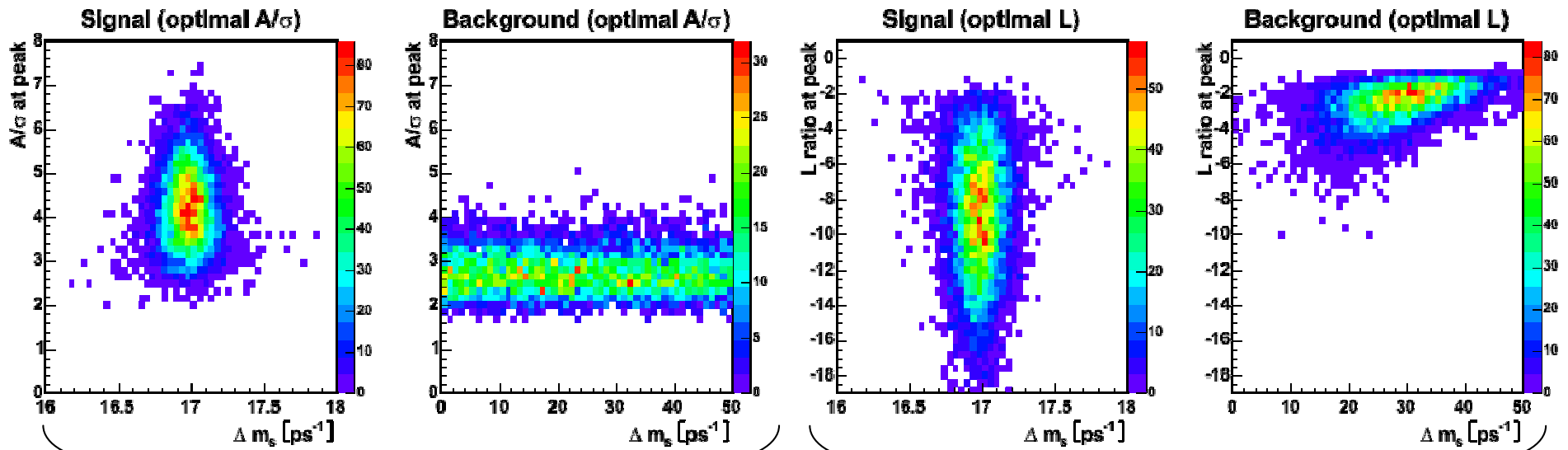
# “Toy” Study

- Based on **full-fledged toy montecarlo**
  - Same efficiency and  $\sigma_{ct}$  as in the first toy
  - Higher statistics (~1500 events)
  - Full tagger set used to derive D distribution
- **Take with a grain of salt**: optimistic assumptions in the toy parameters
- The idea behind this: going **all the way through** with our studies before playing with data



# Distribution of Maxima

- Run toy montecarlo several times
  - “Signal” → default toy
  - “Background” → toy with scrambled taggers
- Apply peak-fitting machinery
- Derive distribution of maxima (position,height)

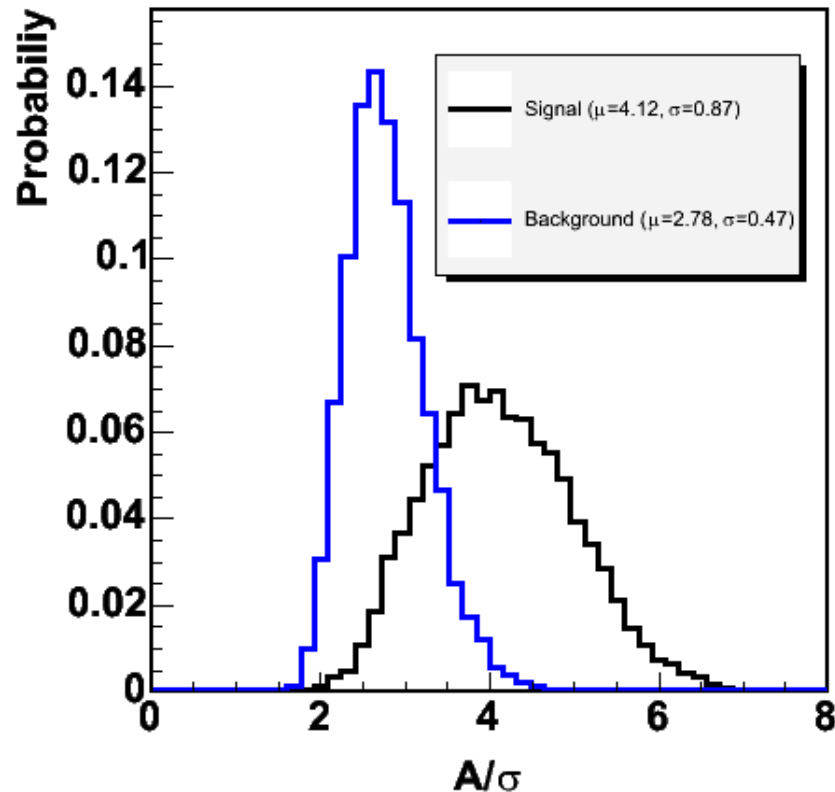


Max  $A/\sigma$ : limited separation and **uniform peak distribution for background**, but not model (&tagger parameter.) dependent

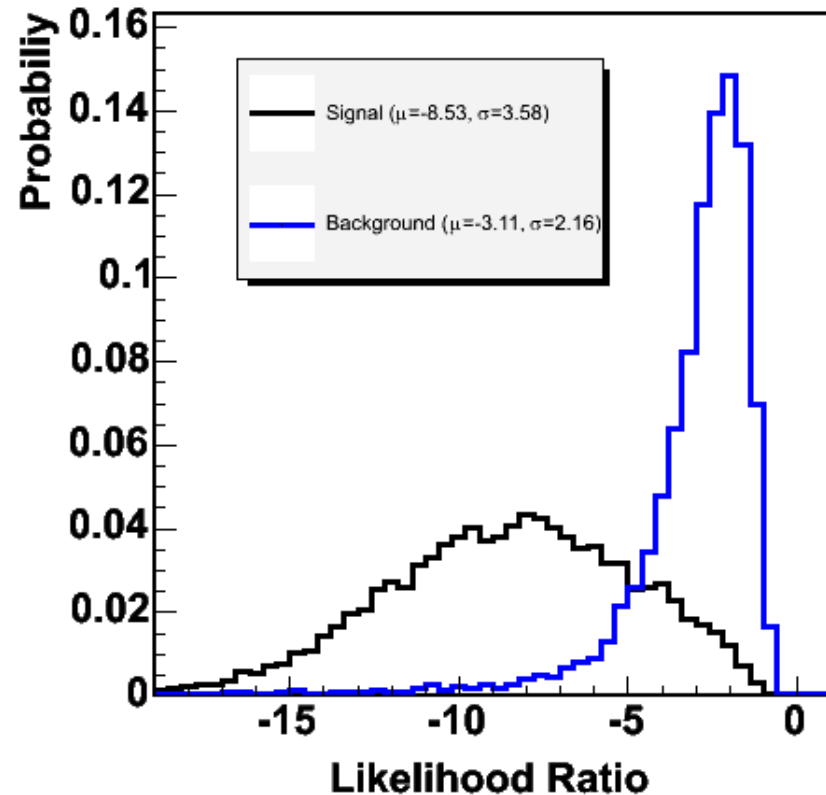
Min log  $L_{\text{ratio}}$ : improved separation and **localized peak distribution for background**

# Maxima Heights

Signal vs Background Maximum Significance



Signal vs Background Minimum Likelihood

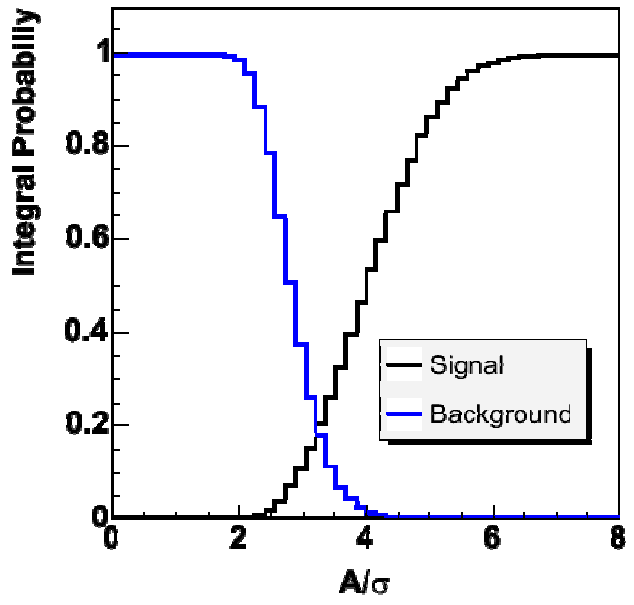


- Separation gets better when more information is added to the “fit”
- Both methods viable “with a grain of salt”. Not advocating one over the other at this point: comparison of them in a real case will be an additional cross check
- ‘False Alarm’ and ‘Discovery’ probabilities can be derived, by integration

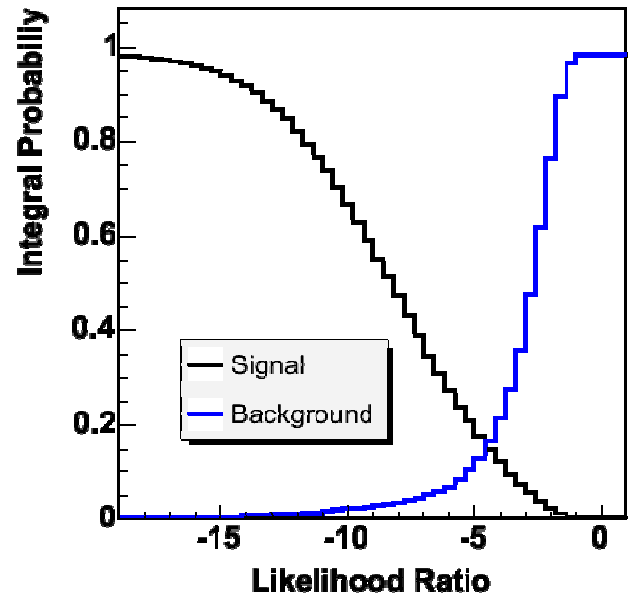
# Integral Distributions of Maxima heights

Linear scale

Signal vs Background Maximum Significance

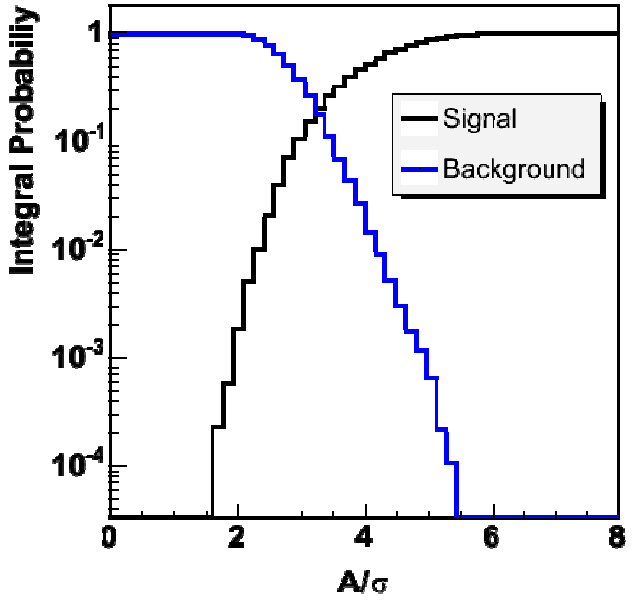


Signal vs Background Minimum Likelihood

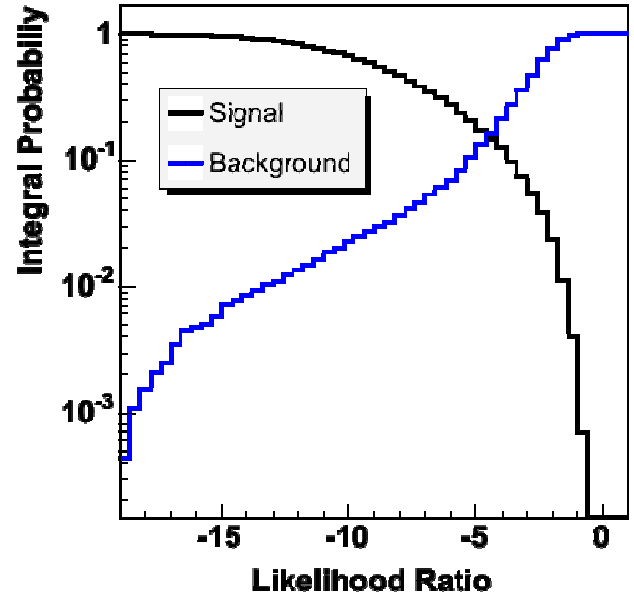


Logarithm. scale

Signal vs Background Maximum Significance



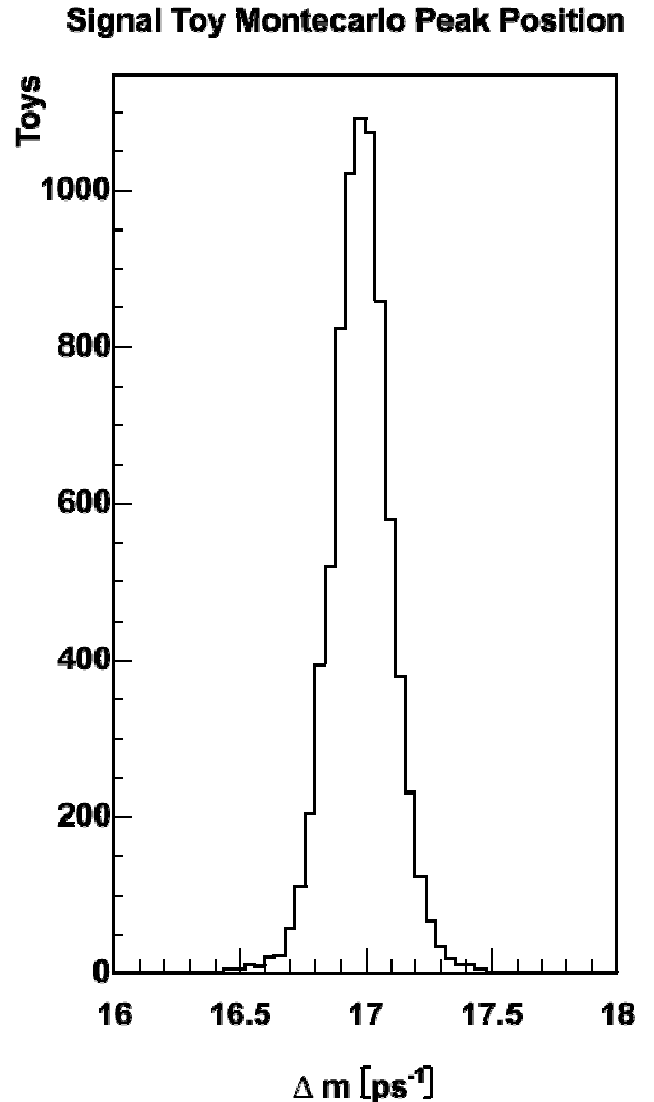
Signal vs Background Minimum Likelihood



# Determining the Peak Position

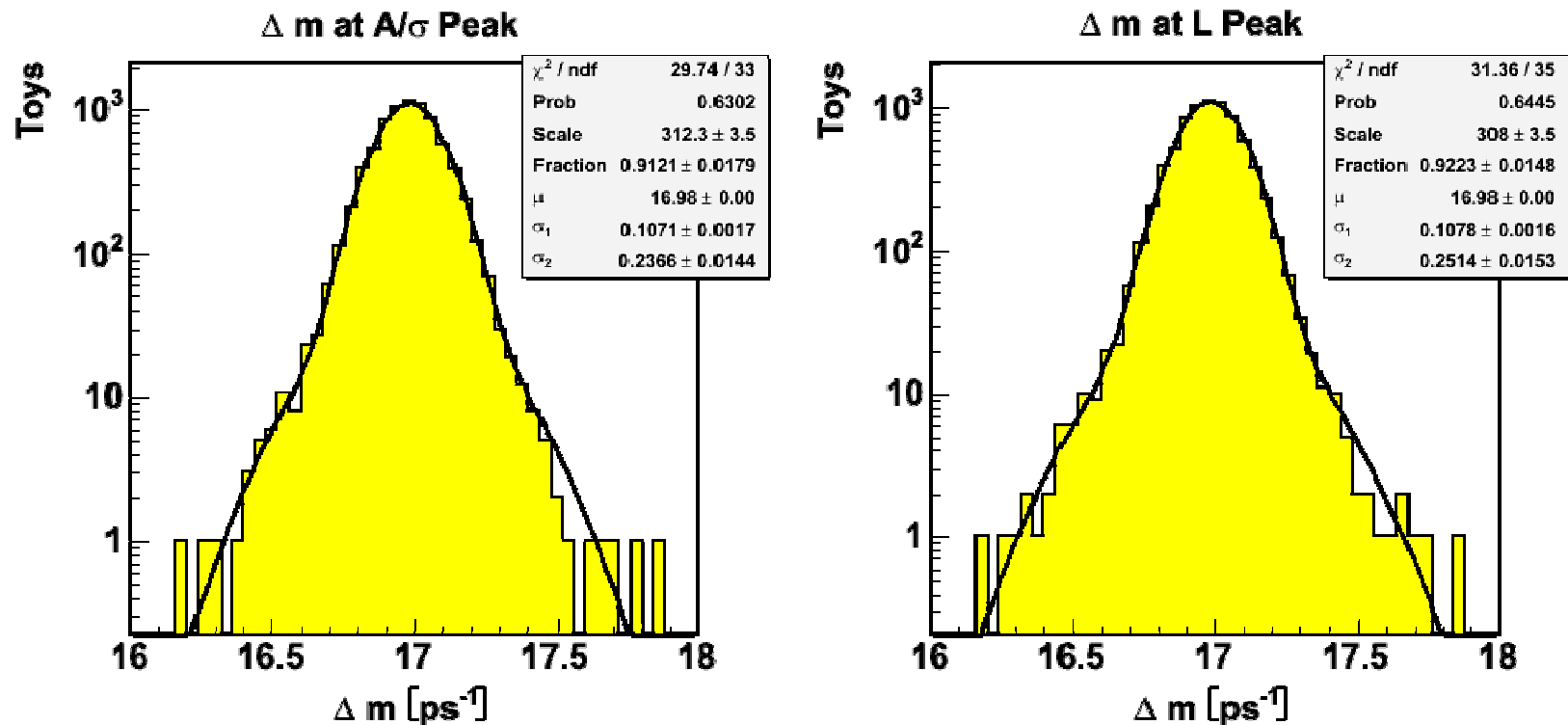
# Measuring the Peak Position

- Two ways of evaluating the stat. uncertainty on the peak position:
  - Bootstrap off data sample
  - Generate toy MC with the same statistics
- At some point will have to decide which one to pick as ‘baseline’ but a cross check is a good thing!
- Example:  $\Delta m_s = 17 \text{ ps}^{-1}$



# Error on Peak Position

- “Peak width” is our goal ( $\sigma_{\Delta m_s}$ )
- Several definitions: histogram RMS, core gaussian, positive+negative fits



- Fit strongly favors two gaussian components
- No evidence for different +/- widths
- The rest, is a matter of taste...

# Next Steps

- **Measure** accurately for the whole  $fb^{-1}$  the ‘**fitter ingredients**’:
  - Efficiency curves
  - Background shape
  - $D$  and  $\sigma_{ct}$  distributions
- Re-generate toy montecarlos and repeat above study all the way through
- Apply same study with blinded data sample
- Be ready to provide result for comparison to main analysis
- Freeze and document the tool, bless as procedure

# Conclusions

- Full-fledged implementation of the Fourier “fitter”
- Accurate toy simulation
- Code scrutinized and mature
- The exercise has been carried all the way through
  - Extensively validated
  - All ingredients are settled
  - Ready for more realistic parameters
  - After that look at data (blinded first)



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