

Event based ML fit for η' data

Methods

- ▶ `TTree::UnbinnedFit()`
- ▶ *RooFit* (WIP)
- ▶ event based fit using BAYESIAN inference
 - ▶ with and without fitting bkg contributions

each case: no measure of "goodness of fit" \rightarrow toy MC necessary (as before)

Remembering PDF to be fitted...

$$-\ln \mathcal{L} = \sum_{i=1}^n -\ln(p_{\text{prompt}}(\phi_i, p_{\gamma,i}, \Sigma, a_1 \dots a_4, b_1 \dots b_4)) + \\ \sum_{j=1}^m -\ln \left(p_{\text{sideband}}(\phi_j, p_{\gamma,j}, \Sigma^{\text{bkg}}, a_1^{\text{bkg}} \dots a_4^{\text{bkg}}, b_1^{\text{bkg}} \dots b_4^{\text{bkg}}) \right)$$

where

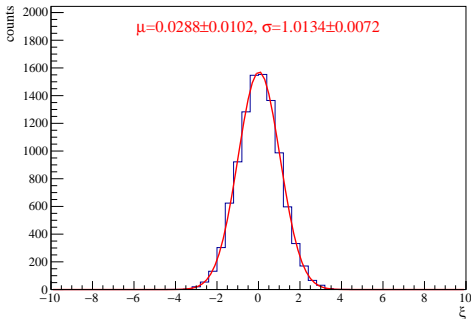
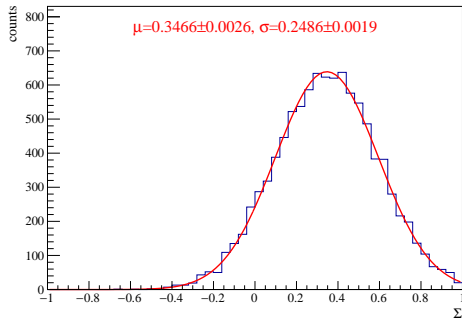
$$p_{\text{prompt}} = f_{\text{sig}} \cdot \tilde{p}(\phi, p_{\gamma}, \Sigma, a_1 \dots a_4, b_1 \dots b_4) \\ + (1 - f_{\text{sig}}) \cdot \tilde{p}(\phi, p_{\gamma}, \Sigma^{\text{bkg}}, a_1^{\text{bkg}} \dots a_4^{\text{bkg}}, b_1^{\text{bkg}} \dots b_4^{\text{bkg}}) \\ p_{\text{sideband}} = \tilde{p}(\phi, p_{\gamma}, \Sigma^{\text{bkg}}, a_1^{\text{bkg}} \dots a_4^{\text{bkg}}, b_1^{\text{bkg}} \dots b_4^{\text{bkg}})$$

and

$$\tilde{p}(\phi, \Sigma) = \frac{\left(1 + p_{\gamma} \Sigma \cos \left(2 \left(\alpha^{\parallel} - \phi\right)\right)\right) \cdot \left(\sum_{k=0}^4 a_k \sin(k\phi) + b_k \cos(k\phi)\right)}{1 - \frac{1}{2} a_2 p_{\gamma} \Sigma}$$

Considering background contributions

- ▶ simulate η' statistics and bkg contributions in toy MC
- ▶ expectation: $\Sigma_{\text{meas}} = a \cdot \Sigma_{\text{true}} + b \cdot \Sigma_{\text{bkg}}$, where $a + b = 1$
- ▶ $\Sigma_{\text{true}} = 0.5, \Sigma_{\text{bkg}} = -0.3, a = 0.8 \rightarrow \Sigma_{\text{meas}} = 0.34$



Considering background contributions

- ▶ If background contribution is known, it can directly be included in the BAYESIAN fit by treating it as "missing data"



$$\tilde{p}(\phi, \Sigma) = \frac{\left(1 + p_\gamma \Sigma \cos\left(2\left(\alpha^\parallel - \phi\right)\right)\right) \cdot \left(\sum_{k=0}^4 a_k \sin(k\phi) + b_k \cos(k\phi)\right)}{1 - \frac{1}{2}a_2 p_\gamma \Sigma}$$

with $\Sigma = (a \cdot \Sigma_{\text{true}} + b \cdot \Sigma_{\text{bkg}})$ and $a, b, \Sigma_{\text{bkg}}$ are read in as data

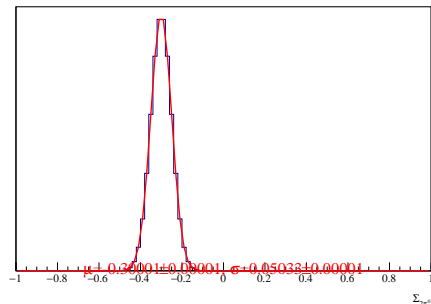
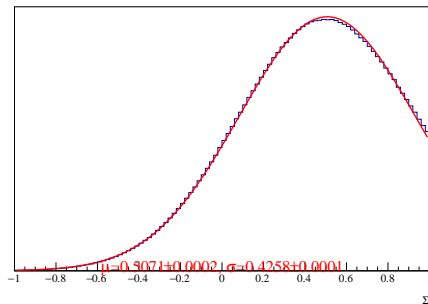
- ▶ statistical error of Σ_{bkg} can be accounted for by fitting an additional unknown parameter $\Sigma_{\text{bkg}}^{\text{true}}$, assuming

$$\Sigma_{\text{bkg}}^{\text{true}} \sim \text{normal}(\Sigma_{\text{bkg}}^{\text{meas}}, \text{err}(\Sigma_{\text{bkg}}^{\text{meas}}))$$

with uniform prior and then using $\Sigma_{\text{bkg}}^{\text{true}}$ as Σ_{bkg} in $p(\phi, \Sigma)$

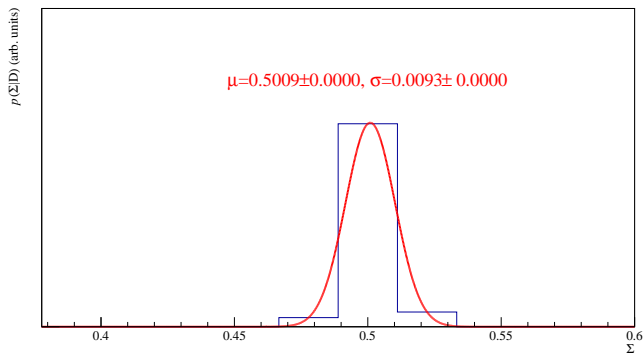
Considering background contributions

toy MC with same dataset as before (assuming $\text{err}(\Sigma_{\text{bkg}}^{\text{meas}}) = 0.05$) reproduces input values very nicely

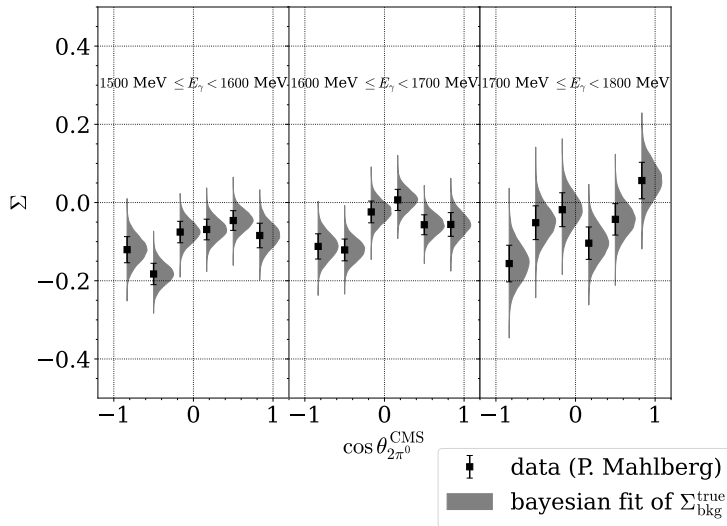


Considering background contributions

Also, likelihood pool combination of posteriors again works nicely



Results



Results

