

Determination of the beam asymmetry Σ in η - and η' -photoproduction using Bayesian statistics

Master thesis for the CBELSA/TAPS collaboration

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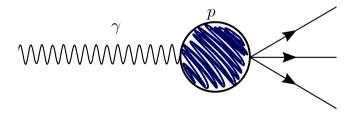
September 22, 2022

Setting the scene

The Standard Model of Particle Physics

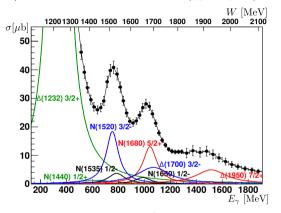
- ▶ matter consists of 12 (anti-)fermions
- ightharpoonup quarks interact via $strong\ interaction$
- \blacktriangleright form bound states: mesons (e.g. $q\bar{q}$) and baryons (e.g. qqq)

baryon spectroscopy (photoproduction) gives insight in strong interaction



Setting the scene

observe resonances N^*/Δ^* in the cross sections $\sigma(\gamma p \to pM)$



Total cross section $\sigma(\gamma p \to p \pi^0)$ [Wunderlich et al. 2017]

→goal: (help to) identify contributing resonances as strong bound states!

- 1. Theoretical basics
- 2. Experimental Setup
- 3. Results

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4. Conclusion

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- ► resonances are broad, overlapping, require complicated partial-wave-analysis (PWA)
- ▶ constraints for the analysis can be derived from polarization observables
- ▶ ultimate goal: "complete experiment"; unambiguous, model-independent PWA solution → several single and double polarization observables needed

Beam-target polarization observables

	target polarization				
photon		x	y	z	
unpolarized	σ_0	-	T	-	
linearly polarized	$-\Sigma$	H	-P	-G	
circularly polarized	-	F	-	-E	

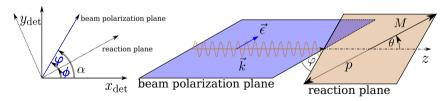
[Sandorfi et al. 2011]

Beam asymmetry Σ

$$\frac{\mathrm{d}\sigma}{\mathrm{d}\Omega}(E_{\gamma},\cos\theta,\varphi) = \frac{\mathrm{d}\sigma}{\mathrm{d}\Omega}(E_{\gamma},\cos\theta) \cdot \left[1 - p_{\gamma}^{\mathrm{lin}} \mathbf{\Sigma} \cos(2\varphi)\right]$$

polarization angle $\varphi=\alpha-\phi$ with $\alpha=\alpha^{\perp/\parallel}=\pm45^\circ,$ polarization degree $p_\gamma^{\rm lin}$

[Sandorfi et al. 2011]



Definition of the polarization angle

- ▶ polarization observables are input for further analysis
- ▶ idea: increase amount of information gained from results using BAYESIAN inference

Bayes' theorem

$$p(\theta|y) \propto p(y|\theta) \cdot p(\theta)$$

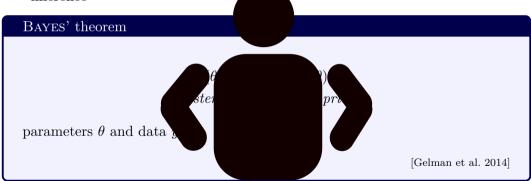
posterior \times likelihood \cdot prior

parameters θ and data y.

[Gelman et al. 2014]

▶ polarization observables are input for further analysis

▶ idea: increase amount of information gained from results using BAYESIAN inference



$$p(\theta|y) \propto p(y|\theta) \cdot p(\theta)$$

▶ prior $p(\theta)$ and likelihood $p(y|\theta)$ can be specified once the model is known \rightarrow gain distributions $p(\theta|y)$ instead of point estimates with error bars

Bayesian parameter inference

For each parameter $\theta_n \in \theta$ we gain marginal posteriors

$$p(\theta_n|y) = \int d\theta_1 \cdots \int d\theta_{n-1} \int d\theta_{n-1} \cdots \int d\theta_N p(\theta_1 \dots \theta_N|y).$$

usually approximated using Markov-Chain Monte Carlo (MCMC) draws $\theta^{(s)}$

[Sivia and Skilling 2005]

 \blacktriangleright all Bayesian fits performed using the *Python* frontend of *Stan*



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- ► MCMC-sampling: adaptive Hamiltonian Monte-Carlo (HMC), i.e. No-U-Turn-Sampling (NUTS)
 - \triangleright generate samples $\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(S)}$ where each $\theta^{(t)}$ depends only on $\theta^{(t-1)}$
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- ▶ diagnosing convergence of MCMC:
 - potential scale reduction statistic $1.00 \lesssim \hat{R} \lesssim 1.01$
 - ► Monte Carlo standard error (MCSE) 'small',

e.g. for mean
$$\mu$$
 MCSE = $\frac{\text{std}(\{\theta^{(s)}\})}{S}$



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 - Monte Carlo standard error (MCSE) 'small', e.g. for mean μ MCSE = $\frac{\text{std}(\{\theta^{(s)}\})}{S}$
- ▶ goodness of fit: posterior predictive checks (PPC)
 - $p(y^{\text{rep}}|y) = \int d\theta p(y^{\text{rep}}|\theta) p(\theta|y)$
 - in practice: $y^{\text{rep},(s)} \sim p(y|\theta^{(s)})$



1. Theoretical basics

2. Experimental Setup

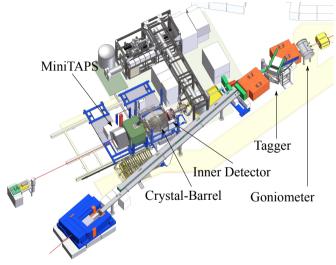
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CBELSA/TAPS experiment

- ▶ generate photon beam from accelerated electrons via bremsstrahlung, with $E_{\gamma} \leq 3.2 \, \text{GeV}$
- ▶ photon beam impinges on liquid hydrogen target: $\gamma p \rightarrow pX \rightarrow pM$
- $\blacktriangleright \ M=\pi^0/\eta/\eta'/\dots$
- ► data set: July-October 2013, 1065 h beam time



Overview of the experimental area, adapted from [Walther 2021]

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Determination of $\Sigma_{\eta'}$

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- \blacktriangleright polarization observables are needed for different final states $(\pi^0, \eta, \eta', \dots)$
- ▶ high precision measurement of beam asymmetry for η production recently published [F. Afzal et al. 2020]
- ▶ goal: confirm results using Bayesian fitting methods

Event selection (η)

analysis performed in 11x12 bins of $(E_{\gamma}, \cos \theta)$ for $\gamma p \to p \eta \to p \gamma \gamma$ by [F. Afzal et al. 2020]

Methods

Remember:
$$\frac{d\sigma}{d\Omega}(E_{\gamma}, \cos\theta, \varphi) = \frac{d\sigma}{d\Omega_0}(E_{\gamma}, \cos\theta) \cdot \left[1 - p_{\gamma}^{\ln \Sigma} \cos(2\varphi)\right]$$

binned fit to event yield asymmetries:

$$A(E_{\gamma},\theta,\phi) = \frac{N^{\perp}(E_{\gamma},\theta,\phi) - N^{\parallel}(E_{\gamma},\theta,\phi)}{p_{\gamma}^{\parallel}N^{\perp}(E_{\gamma},\theta,\phi) + p_{\gamma}^{\perp}N^{\parallel}(E_{\gamma},\theta,\phi)} = \Sigma(E_{\gamma},\theta)\cos\left(2\left(\alpha^{\parallel}-\phi\right)\right)$$

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Methods

remember:
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unbinned maximum likelihood fit:

$$\tilde{p}(\phi, \Sigma) = \frac{\left(1 + p_{\gamma} \Sigma \cos\left(2\left(\alpha^{\parallel} - \phi\right)\right)\right) \cdot \epsilon\left(\phi\right)}{C}$$

applying Bayesian approach to event yield asymmetries:

▶ assume Gaussian errors, i.e.

$$A(\phi) = \Sigma \cos \left(2\left(\alpha^{\parallel} - \phi\right)\right) + \epsilon$$

where $\epsilon \sim \mathcal{N}(0, \sigma)$

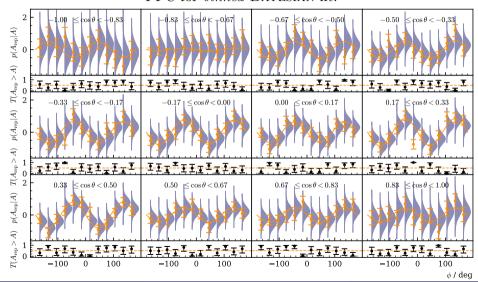
▶ likelihood $p(A|\Sigma)$ of given by

$$y_i \sim \mathcal{N}\left(\Sigma \cos\left(2\left(\alpha^{\parallel} - \phi_i\right)\right), \sigma_i\right)$$
 $\mathcal{L} = \prod_i p(y_i|\theta)$

▶ prior:

$$p(\Sigma) \sim \mathcal{N}(0,1)_{[-1,1]}$$

Sample from posterior $p(\Sigma|A) \propto p(A|\Sigma) \cdot p(\Sigma)$!

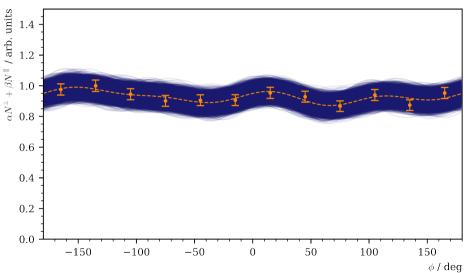


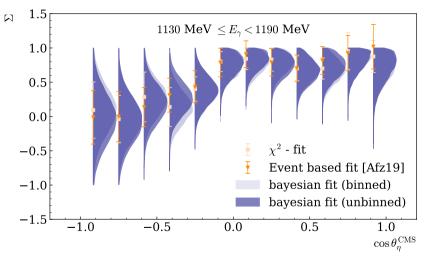
applying Bayesian approach to unbinned fit:

- ▶ event based likelihood given by product of all single-event likelihoods
- ▶ assign priors for all fit parameters (18 in total)
- \blacktriangleright truncate beam asymmetry to allowed region [-1,1]
- ▶ perform toy Monte Carlo experiments

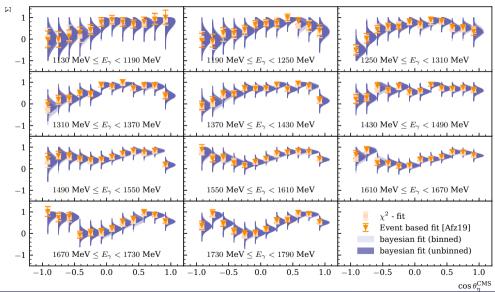
Sample from posterior!

PPC for unbinned BAYESIAN fit:





Distinct advantage: sample only in physically allowed parameter space



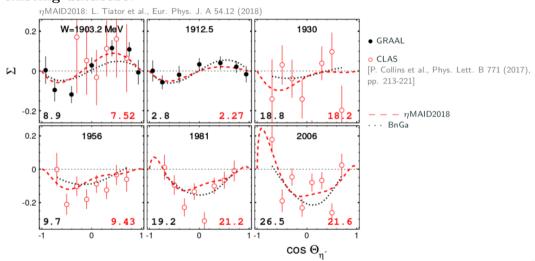
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Determining the beam asymmetry in η' photoproduction existing database:



First, perform event selection regarding η' photoproduction

η'	
Decay mode	Branching ratio
$\pi^+\pi^-\eta$	42.6%
$ ho^0 \gamma (o \pi^+ \pi^- \gamma)$	28.9%~(28.9%)
$\pi^0\pi^0\eta(o 6\gamma)$	$22.8\% \ (8.8\%)$
$\omega\gamma(\to\pi^+\pi^-\pi^0\gamma/\pi^0\gamma\gamma)$	$2.52\% \ (2.2\%/0.21\%)$
$\gamma\gamma$	2.3%

[Workman et al. 2022]

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$\gamma\gamma$	2.3%

[Workman et al. 2022]

event selection:

analysis performed in 3x6 bins of
$$(E_{\gamma}, \cos \theta)$$
 for $\gamma p \to p \eta' \to p \gamma \gamma$,
$$E_{\gamma} \in [1500, 1800] \text{ MeV}$$

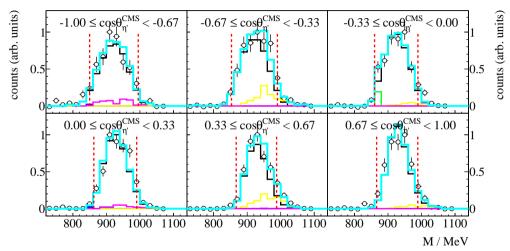
$$= p_{\eta'} + p_{\text{recoil}}$$

$$= \underbrace{p_{\gamma_1} + p_{\gamma_2}}_{=p_{\eta'}} + p_{\text{recoil}}$$

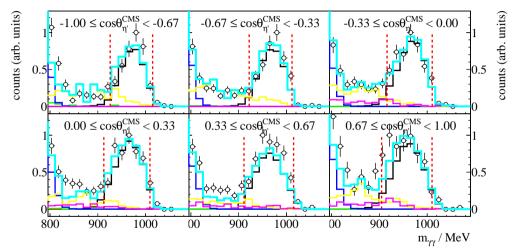
$$= \underbrace{p_{\gamma_1} + p_{\gamma_2}}_{=p_{\eta'}} + p_X$$

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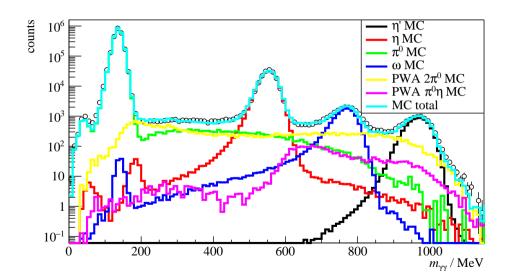
- \blacktriangleright one charged, two uncharged detector hits in coincidence with beam γ
- ► Coplanarity $\Delta \phi = \phi_{\eta'} \phi_{\text{recoil}} \stackrel{!}{=} 180^{\circ}$
- ▶ Polar angle $\theta_X \stackrel{!}{=} \theta_{\text{recoil}}$
- ▶ Missing mass $m_X \stackrel{!}{=} m_p$
- ► Invariant mass $m_{\gamma\gamma} \stackrel{!}{=} m_{\eta'}$



data points: m_X , MC histograms: total, $p\eta'$, $p2\pi^0$, $p\pi^0\eta$

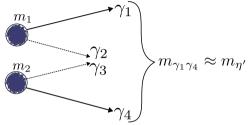


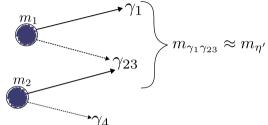
data points: $m_{\gamma\gamma}$, data points: m_X , MC histograms: total, $p\eta'$, $p2\pi^0$, $p\pi^0\eta$, $p\omega$



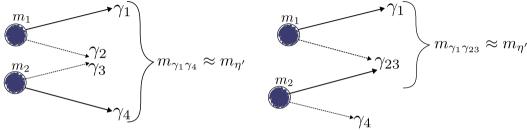
Determining the beam asymmetry in η' photoproduction why these contributions from 4γ final states $2\pi^0$ (and $\pi^0\eta$)??

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acceptance for $2\pi^0$ events is almost vanishing $A(E_{\gamma}, \cos \theta) < 2 \cdot 10^{-3}$, yet

$$R = \frac{\sigma_{2\pi^{0}} \cdot BR_{2\pi^{0} \to \gamma\gamma} \cdot \tilde{A}_{2\pi^{0}}}{\sigma_{n'} \cdot BR_{n' \to \gamma\gamma} \cdot \tilde{A}_{n'}} = \frac{5 \,\mu b \cdot 0.9765 \cdot 2 \cdot 10^{-3}}{1 \,\mu b \cdot 0.023 \cdot 0.61} \approx 0.7!$$

explains high background contributions of up to 45% (background to total)

[Workman et al. 2022; Crede et al. 2009; Dieterle et al. 2020]

How do we get rid of background contributions?

▶ real photons mimic a two-photon final state, no sensible additional cuts have been found

How do we get rid of background contributions?

- ▶ real photons mimic a two-photon final state, no sensible additional cuts have been found
- \blacktriangleright main background from $2\pi^0$ photoproduction
- ▶ beam asymmetry for this reaction determined by [Mahlberg 2022]
- \blacktriangleright correct estimates for Σ according to the amount of background

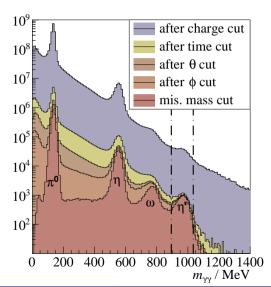
$$\Sigma^{\text{meas}} = (1 - \delta) \cdot \Sigma_{\eta'} + \delta \Sigma_{2\pi^0}$$

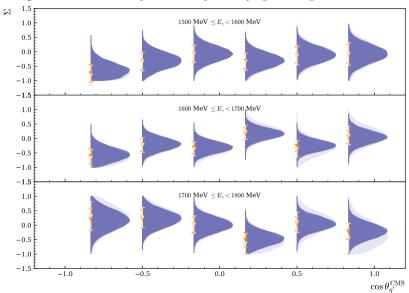
total: $\sim 8000 \ \eta' \rightarrow \gamma \gamma$ events

- ▶ perform unbinned fit as maximum likelihood fit and BAYESIAN fit
- ► BAYESIAN fit: modify likelihood

$$\tilde{p}\left(\phi, \Sigma\right) \to \tilde{p}\left(\phi, (1 - \delta)\Sigma_{1} + \delta\Sigma_{2}^{true}\right)$$
$$\Sigma_{2}^{true} \sim \mathcal{N}(\Sigma_{2}^{meas}, \tau)$$

▶ unbinned maximum likelihood fit: shift point estimates *after fit*





Systematic error:
$$\Delta \Sigma_{\eta'}^{\text{sys}} = \sqrt{\left(\frac{\Delta p_{\gamma}}{p_{\gamma}} \Sigma_{\eta'}\right)^2 + \left(\Delta \Sigma_{\eta'}\right)^2}$$
.

▶ polarization degree

$$\frac{\Delta p_{\gamma}}{p_{\gamma}} = \begin{cases} 0.05 & E_{\gamma} < 1600 \,\text{MeV}, \\ 0.08 & \text{otherwise} \end{cases}$$

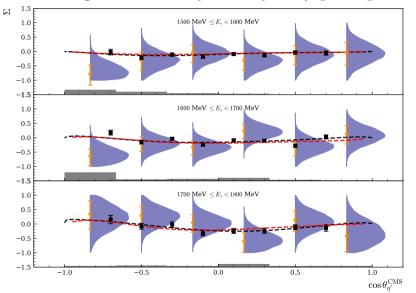
▶ background contributions

$$\Sigma^{\text{meas}} = (1 - \delta_1 - \delta_2) \cdot \Sigma_{n'} + \delta_1 \Sigma_{2\pi^0} + \delta_2 \Sigma^{\text{r bkg}},$$

thus:

$$\Delta\Sigma_{\eta'} = \max \left[\left| \frac{\Sigma^{\text{meas}} - \delta_1 \cdot \Sigma_{2\pi^0} \pm \delta_2 \cdot 1}{1 - \delta_1 - \delta_2} - \frac{\Sigma^{\text{meas}} - \delta \cdot \Sigma_{2\pi^0}}{1 - \delta} \right| \right]$$

[F. N. Afzal 2019; Eberhardt 2012]



- measurement at CLAS [Collins et al. 2017] .
- - etaMAID PWA [Tiator et al. 2018],
- --- BnGa PWA
 [Anisovich et al.
 2018]

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Conclusion

Summary

- \triangleright Σ extracted for η and η' final state
- $ightharpoonup \eta$ results obtained with BAYESIAN fit agree with previous results
- $\rightarrow \eta'$ results agree with previous measurements

Outlook

- ► use posterior *distributions* for PWA calculations
- ▶ increase precision of existing data , i.e. investigate $\eta' \to \pi^0 \pi^0 \eta$
- \blacktriangleright measurement of observables near η' production threshold

BACKUP & REFERENCES

Additional theoretical basics

Unpolarized differential cross section

$$\frac{\mathrm{d}\sigma}{\mathrm{d}\Omega} = \frac{1}{4}\rho \sum_{\mathrm{spins}} |\langle f|\mathcal{F}|i\rangle|^2,$$

where

$$\mathcal{F} = i(\vec{\sigma} \cdot \vec{\epsilon})F_1 + (\vec{\sigma} \cdot \hat{q})(\vec{\sigma} \cdot (\hat{k} \times \vec{\epsilon}))F_2 + i(\vec{\sigma} \cdot \hat{k})(\hat{q} \cdot \vec{\epsilon})F_3 + i(\vec{\sigma} \cdot \hat{q})(\hat{q} \cdot \vec{\epsilon})F_4$$

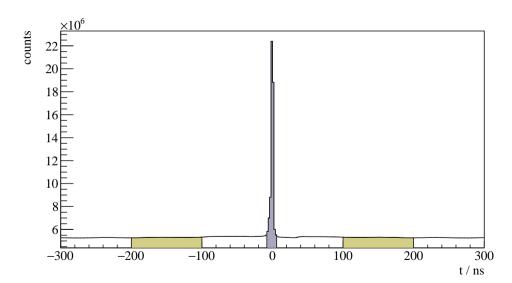
 F_i : complex CGLN Amplitudes

[Chew et al. 1957]

 $\frac{d\sigma}{d\Omega} \in \mathbb{R}$, not sufficient do determine \mathcal{F} unambiguously

 \rightarrow Polarization Observables can be related to F_i

Time cut



Full PDF for unbinned maximum likelihood fit

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

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

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

Hamiltonian Monte Carlo

Introduce artificial "momentum" ϕ

$$\begin{split} p(\boldsymbol{\theta}, \boldsymbol{\phi}|y) &= p(\boldsymbol{\theta}|y) \cdot p(\boldsymbol{\phi}|\boldsymbol{\theta}, y) = p(\boldsymbol{\theta}|y) \cdot p(\boldsymbol{\phi}) \\ \Leftrightarrow -\log p(\boldsymbol{\theta}, \boldsymbol{\phi}|y) &= -\log p(\boldsymbol{\theta}|y) - \log p(\boldsymbol{\phi}) \\ &\overset{\mathrm{Def.}}{\Leftrightarrow} H(\boldsymbol{\theta}, \boldsymbol{\phi}) := V(\boldsymbol{\theta}) + T(\boldsymbol{\phi}), \end{split}$$

Applying the well known equations of motion to this Hamiltonian one finds

$$\frac{\mathrm{d}\theta_i}{\mathrm{d}t} = \frac{\partial H}{\partial \phi_i} = \frac{\partial T}{\partial \phi_i} \qquad \qquad \frac{\mathrm{d}\phi_i}{\mathrm{d}t} = -\frac{\partial H}{\partial \theta_i} = -\frac{\partial V}{\partial \theta_i}.$$

Integrate to arrive at proposals θ^*, ϕ^* fed into METROPOLIS-HASTINGS accept-reject step

Diagnostics of a Bayesian fit I

The \widehat{R} -statistic is defined for a set of M MARKOV chains $\boldsymbol{\theta}_m$ with N samples $\boldsymbol{\theta}_m^{(n)}$. The between-chain-variance B is estimated as

$$B = \frac{N}{M-1} \sum_{m=1}^{M} \left(\bar{\boldsymbol{\theta}}_{m}^{(\bullet)} - \bar{\boldsymbol{\theta}}_{\bullet}^{(\bullet)} \right)^{2},$$

where

$$ar{m{ heta}}_m^{(ullet)} = rac{1}{N} \sum_{n=1}^N m{ heta}_m^{(n)}, \qquad \qquad ar{m{ heta}}_{ullet}^{(ullet)} = rac{1}{M} \sum_{m=1}^M ar{m{ heta}}_m^{(ullet)}.$$

Further the within-chain variance W is averaged over all chains

$$W = \frac{1}{M} \sum_{m=1}^{M} s_m^2,$$

Diagnostics of a Bayesian fit II

where

$$s_m^2 = \frac{1}{N-1} \sum_{n=1}^N \left(\boldsymbol{\theta}_m^{(n)} - \bar{\boldsymbol{\theta}}_m^{(\bullet)} \right)^2.$$

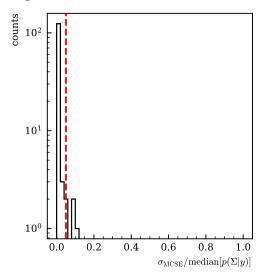
Combining the between and within chain variances into the variance estimator

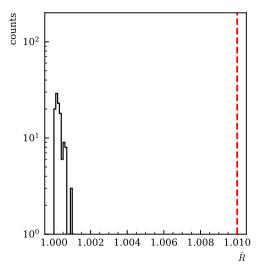
$$\widehat{\operatorname{var}}^+(\boldsymbol{\theta}|y) = \frac{N-1}{N}W + \frac{1}{N}B$$

one finally arrives at the potential scale reduction statistic

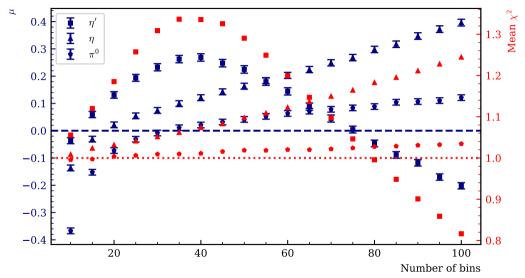
$$\widehat{R} = \sqrt{\frac{\widehat{\operatorname{var}}^+(\boldsymbol{\theta}|y)}{W}}.$$

Diagnosis of the unbinned BAYESIAN fit

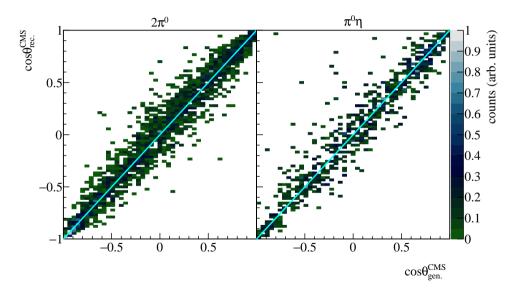




Systematic effects of binned fitting



$\cos\theta(4\gamma)$ vs. $\cos\theta(2\gamma)$



References I

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