B05 – A novel approach to the baryon spectrum based on stochastic methods

NuMeriQS Retreat

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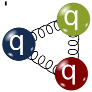
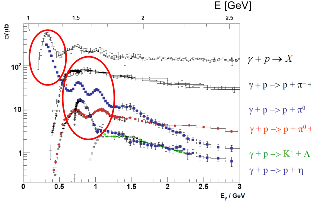
Baryon spectroscopy

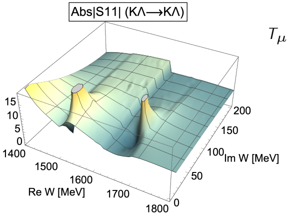


Extract the spectrum of excited states from experimental data

$\rightarrow$ What are those bumps?



- energy & angular momentum excitations of baryons **(resonances)**?
- conventional 3 quark baryons or more complicated objects?
- ...



source: ELSA; data: ELSA, JLab, MAMI

- **Theoretical challenge**: build a model that includes as many constraints from symmetries of nature as possible

$$T_{\mu\nu}(q, p', W) = V_{\mu\nu}(q, p', W) + \sum_\kappa \int_0^\infty dp\, p^2\, V_{\mu\kappa}(q, p, W) G_\kappa(p, W)\, T_{\kappa\nu}(p, p', W)$$

- **Numerical challenge**: large number of free model parameters, heterogeneous data base, uncertainty quantification, ...

> $\rightarrow$ use HMC and Bayesian inference to sample parameter space
>
> $\rightarrow$ determine resonance uncertainties from samples (means, standard deviation)

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Bayesian parameter estimation with HMC

Bayes':

$$\log \pi(\theta \mid D) \;\propto\; \log L(D \mid \theta) \;+\; \log \pi(\theta) = -\tfrac{1}{2}\chi^2(D,\theta) \;+\; \log \pi(\theta)$$

$D \sim$ data
$\theta \sim$ vector of model parameters, dim$\sim$ 900
(assumed gaussian likelihood)

Hamilton's equations:

with $H = \frac{1}{2} p^T M^{-1} p + \frac{1}{2}\chi^2(\theta)$

$$\frac{d\theta}{dt} = M^{-1} p \;\;, \quad \frac{dp}{dt} = \nabla_{\theta_i}\left(\frac{1}{2}\chi^2(\theta) - \log \pi(\theta)\right)$$

- leapfrog to propose updates for the Markov chain $\rightarrow$ need numerical gradient of $\chi^2(\theta)$ (costly in high-dim parameter space)

  Idea: reevaluate gradient only every n-th step?
- Mass matrix M (parameters are highly correlated)

  $\rightarrow$ ($M = 1$,) $M = diag(Cov(\theta))$ or $M = Cov(\theta)$ (from warm-up phase, Euclidean HMC)?

  or beyond "vanilla" HMC: Riemannian kinetic energy?
- Integration time: $\rightarrow$ hand-tuned to achieve a good acceptance rate

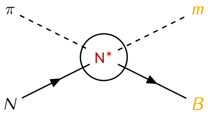
  or beyond "vanilla" HMC: No-U-Turn sampler

Further challenges specific to our problem

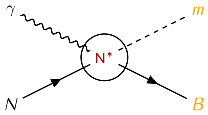
(Besides the costly gradient)

- Diverse data base, different production mechanisms:

πN scattering



photoproduction



partially inconsistent data, very different quantity & quality
$\rightarrow$ weights in χ^2 to account for limited # of data points
(so far: adjusted as needed to achieve a good description of all data)

- Identify pathological solutions: good χ^2 but "unatural" amplitudes (sharp rises/drops, wiggles)
  $\rightarrow$ penalties?
- **Systematic uncertainties**:. model uncertainties as, e.g, # of resonance states
  $\rightarrow$ Bayesian evidence for model w/ vs. w/o a certain state
  $\rightarrow$ full HMC run for model w/o state?
- Practical challenge: hand-coded HMC in Fortran 90