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Machine Learning aided pole localization for the $a_0(980)$ resonance - status of the project.

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Plan

- What is it all about ? (aka Motivation)
- Physics employed
- Some preliminary results
- How ML may contribute ?

Motivation

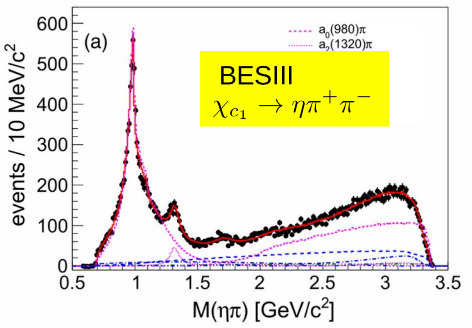
- We analyze the open charm (D_s^+) and charmonia (η_c, χ_{c1}) hadronic decays into final states where the $a_0(980)$ resonance is observed in the $\pi\eta$ mass distribution,
- $a_0(980)$ along with $f_0(980)$ are the mesons that escape straightforward interpretation within naive quark model:
  - $q\bar{q}$ interpretation is unlikely,
  - Tetraquark (compact structure) or $K\overline{K}$ meson molecule (loose structure) interpretations are deliberated,
- the shape of both resonance lines is strongly influenced by the close presence of the $K\overline{K}$ threshold
- *Importantly* these features are replicated in the *c* and *b* quark sector, so the tools developed for $a_0(980)$ and interesting by itself, may be carried over to studying near threshold dynamics in heavier sectors.

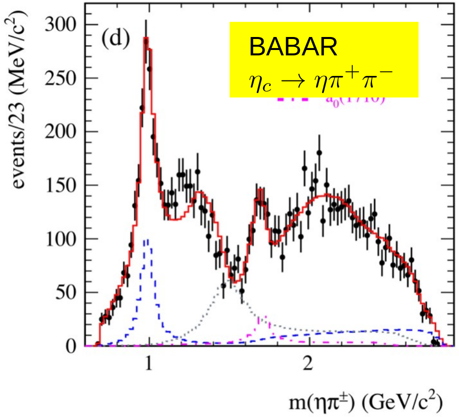
Motivation

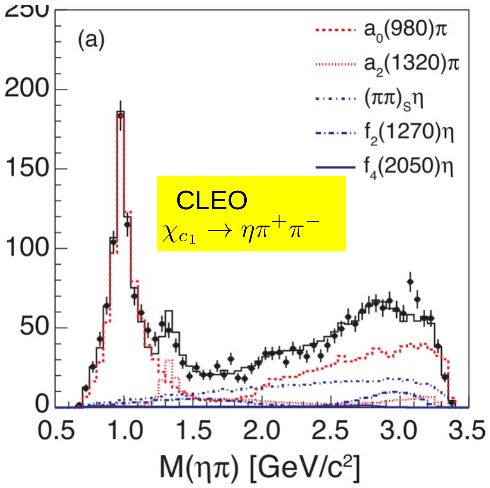
- Role of analytical structure and singularities – no singularity occurs without the reason:
  - Poles define the masses (and widths/lifetimes) of bound states (and resonances)
  - Cuts define thresholds in either direct or crossed channels
  - Localizing the poles corresponding to $a_0(980)$ is our prime objective
- Practically, the positions of poles in the complex energy/momentum plane are model dependent;
- Experiments exploit different resonance production mechanisms, operate at various energy resolutions and have different background subtraction strategies;
- Approaches based on the ML allow for elaborating the common strategy to reconcile some of these difficulties, in particular:
  - Treat models at hand on the same footing
  - Put data from different experiments in the same analysis framework (reduce bias)

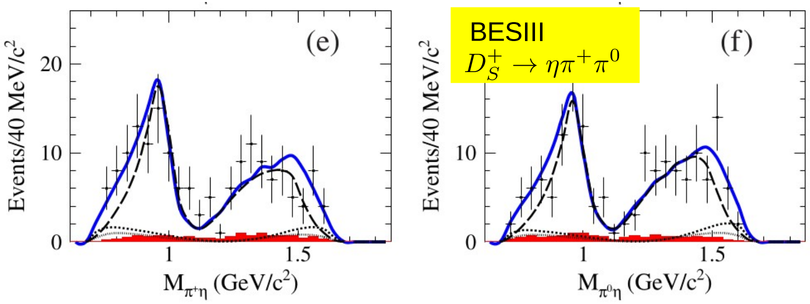
Motivation

- Specifically, we look at these data:









Obviously the mass resolutions, useful bin numbers and backgrounds differ considerably.

Physics employed

We use two explicitly unitary models to describe the data:

1. Coupled channel model in the scattering length approximation (Model 1):

   Frazer, Hendry, PhysRev. 134, 6B (1964),

   C. Fernández-Ramírez et al. (JPAC), Phys. Rev. Lett. 123 (2019), 092001

   L. Ng et al. (JPAC) Phys.Rev.D 105 (2022) 9, L091501

   Minimal theoretical assumptions but is the scattering length approximation good enough ?

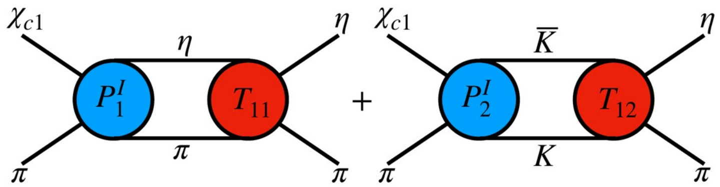
2. Coupled channel model with the interaction parametrized in terms of separable potentials (Model 2):

   Leśniak, Acta. Phys. Pol. B 27, 8, 1835 (1996)

   Furman, Leśniak, Phys. Lett. B 538, 3–4, 266-274 (2002)

   No kinematical approximations but microscopical interpretation not evident.

Physics employed



We use coupled channel $\pi\eta$ unnormalized differential intensity as the sole observable

$$dI/dE = \rho(s)\left[|P_1(s)T_{11} + P_2(s)T_{12}|^2 + B(s)\right],$$

where $\rho(s) = Mpq \quad p = \lambda^{\frac{1}{2}}(s, M^2, m_s^2)/2M, \quad q = \lambda^{\frac{1}{2}}(s, m_\pi^2, m_\eta^2)/2\sqrt{s}$

$P_1(s), P_2(s)$ and $B(s)$ are 1st-degree polynomials describing the heavy meson - $\pi\eta$, heavy meson $K\overline{K}$ and incoherent background, respectively.

Observations:

1. We have 2 channels, thus 4 Riemann sheets in the complex energy/momentum plane

2. Practical fits show that this model is even too flexible - dropping the background and putting constants for $P_1(s)$ and $P_2(s)$ suffices.

Physics employed

- Model 1:
  We start from the inverse amplitude matrix. where the rhs is scattering length approximated:

$$\hat{T}^{-1} = \hat{c} - i\hat{k}$$

- From this the elastic and transition amplitudes read:

$$T_{11} = \frac{c_{22} - ik_2}{(c_{11} - ik_1)(c_{22} - ik_2) - c_{12}^2}$$

$$T_{12} = \frac{-c_{12}}{(c_{11} - ik_1)(c_{22} - ik_2) - c_{12}^2}$$

Observation: Poles we are looking for are just zeros of denominators of T_{11} and T_{12}

- There are some guidelines from the theory:

  1) There are only 4 poles
  2) They may be only on the 2nd and 4th Riemann sheets (or exceptionally on the 1st – bound state)

Physics employed

- Model 2 (just a glimpse, TL;DR)

Why separable potentials ?

$$T_{ij}(p,p';E) = V_{ij}(p,p') + \sum_k \int_0^\infty dq\, q^2\, V_{ik}(p,q)\, G_k(E,q)\, T_{kj}(q,p';E)$$

Coupled channel Lippmann-Schwinger equation is hard to solve.

But if we assume a separable form of the potential

$$V_{ij}(p,p') = \sum_{\alpha,\beta=1}^{N} g_i^{(\alpha)}(p)\, \lambda_{\alpha\beta}\, g_j^{(\beta)}(p')$$

things start to simplify considerably, because the amplitude also becomes separable

$$T_{ij}(p,p';E) = \sum_{\alpha,\beta=1}^{N} g_i^{(\alpha)}(p)\, \tau_{\alpha\beta}(E)\, g_j^{(\beta)}(p')$$

This turns the integral equation into algebraic one and the solution is:

$$\boldsymbol{\tau}(E) = \left[\boldsymbol{\lambda}^{-1} - \mathbf{I}(E)\right]^{-1} \quad \text{with} \quad I_{\alpha\beta}(E) = \sum_k \int_0^\infty dq\, q^2\, g_k^{(\alpha)}(q)\, G_k(E,q)\, g_k^{(\beta)}(q)$$

Physics employed

- Model 2 (continued)

  The S-matrix can be related to the ratio of Jost functions

  $$S(E) \; = \; \frac{F(\pm k_1, \pm k_2)}{F(+k_1, +k_2)}$$

  while the Jost function is proportional to the determinant of (algebraic) L-S equation kernel

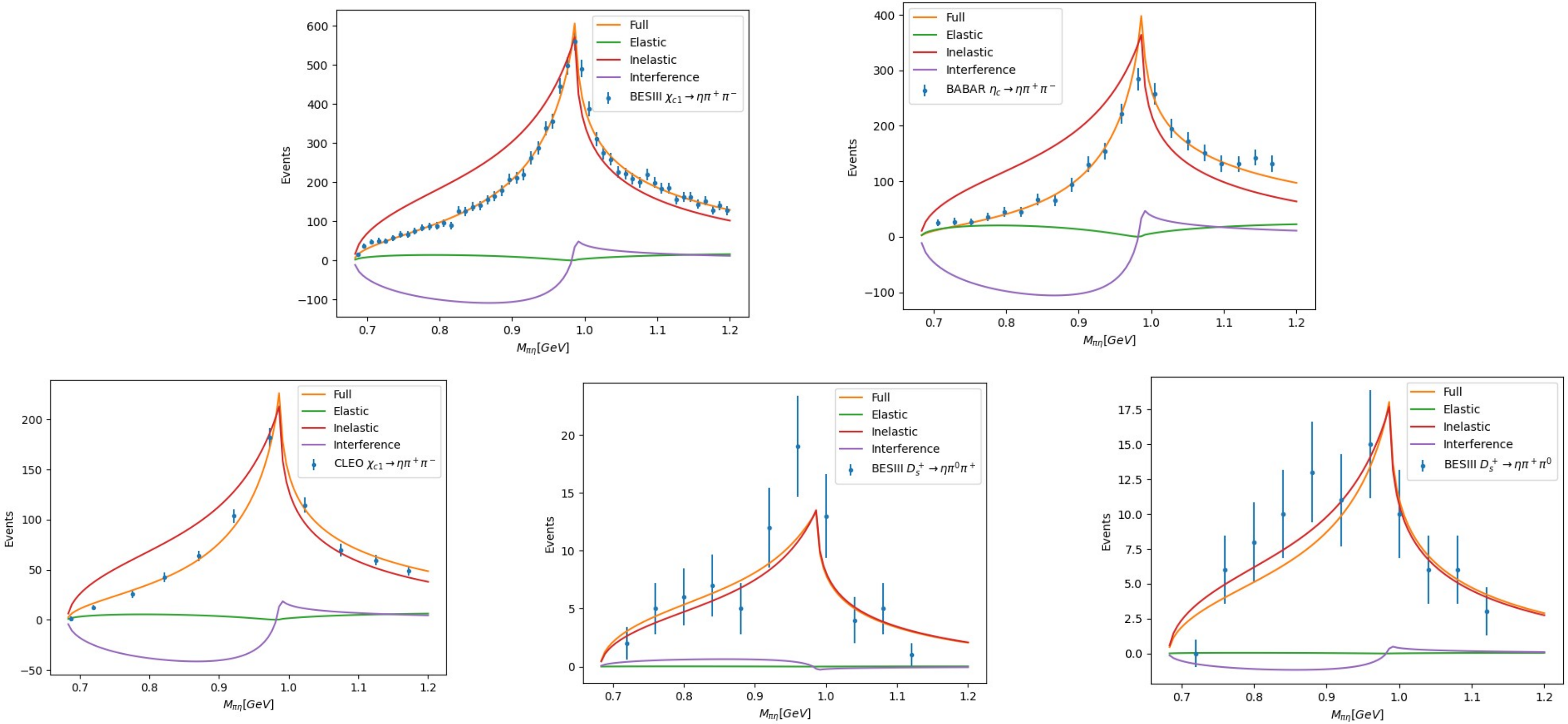
  $$F(k_1, k_2) \propto det[\lambda^{-1} - \boldsymbol{I}(E)]$$

  All this boils down to the observation that the poles of the amplitude are just zeros of the Jost function.

- Observations:
  - Jost function is admittedly more complex than rank-4 polynomial (we don’t know how many zeros are there)
  - We did not use any kinematical (scattering length) approximation

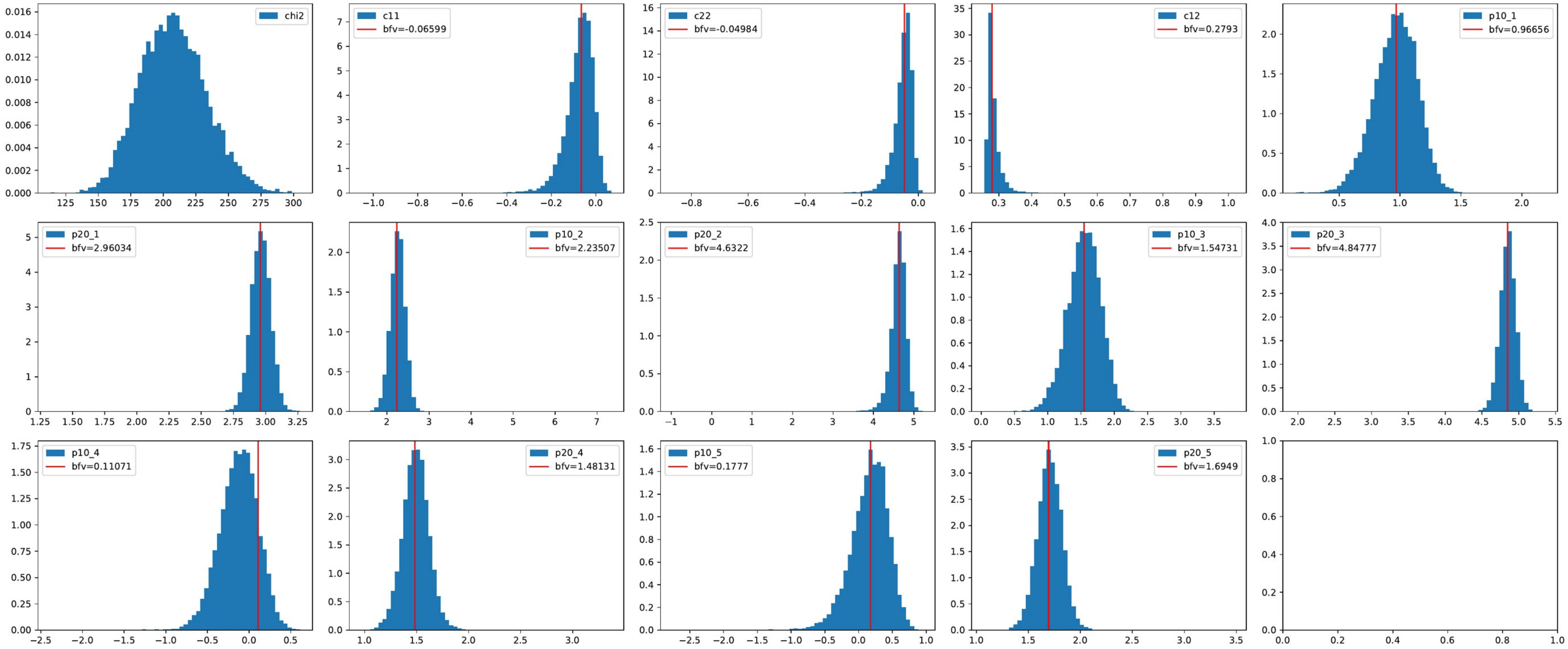
Some preliminary results

- Fits of Model 1 to the data



Some preliminary results

- Parameter values



OK, Model 1 seems to fit the data.
What next ?

How ML may contribute ?

Plan:

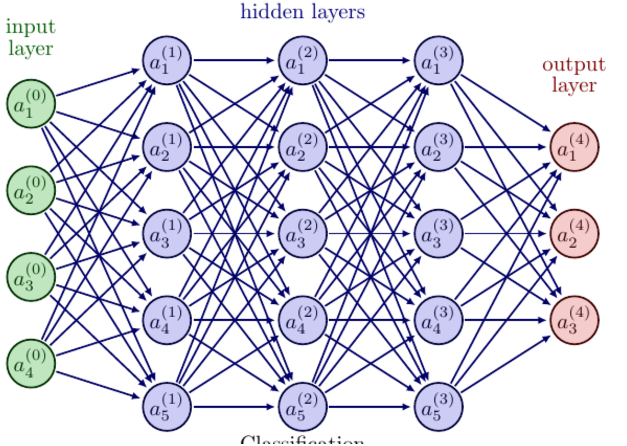
1. Take the model and generate the synthetic intensities sampling the model parameters from some reasonable interval
2. For each tuple of params compute pole locations
3. Add Gaussian noise to the intensity to mimic experimental uncertainty
4. Put intensity on the neural network input and the pole locations on the network's output
5. Use appropriate loss function (Euclidean distance and/or cosine distance) to measure the distance of predicted poles to true ones.
6. Minimize the loss
7. Bootstrap experimental data and predict the distribution of "real" (experiment based) pole locations

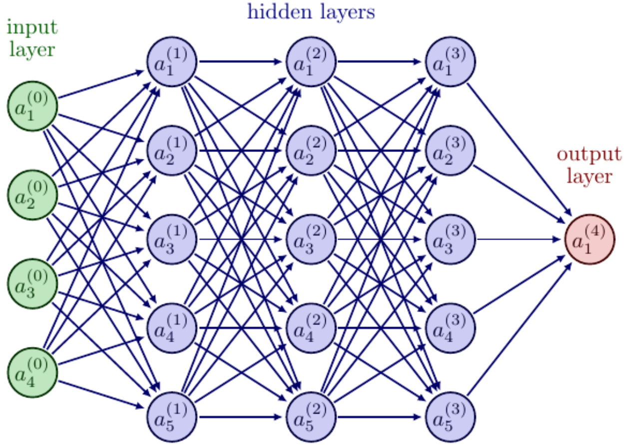
But which neural network ?

How ML may contribute ?

Dense feed forward ANN is no good

- It requires constant length input
- Does not understand the local data context (increase, decrease, extrema)
- Does not understand the global data context (big bump after the small bump or other way around)
- Such networks generalize poorly



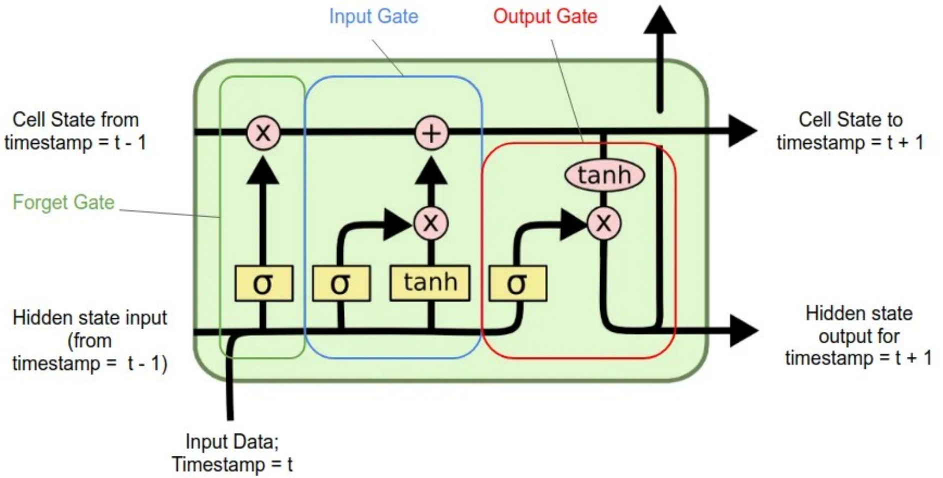


Regression

How ML may contribute ?

- Recurrent Neural Network (RNN) is an answer. In fact we will use it’s refined version called Long Short-Term Memory (LSTM)

- Key components:
- Cell state (Ct) – the long-term memory stream.
- Forget gate (ft) – decides what information to erase.
- Input gate (it) – decides what new information to write.
- Candidate vector (Ĉt) – potential new cell content.
- Output gate (ot) – controls what information becomes the hidden state (ht).



How ML may contribute ?

Initial tests passed:

- The model locates the poles of toy rational functions
- Early tests on the Model 1 encouraging

I will give conclusions and outlook
once we finish

Thank you for your attention !