Future Directions in Spectroscopy Aanalysis (FDSA2024)
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Lineshape of the $f_0(980)$

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Outlook

Motivation

- Compact or molecule?
- Probably a mix. Interest on the dominant contribution
- PDG'22: Section 64. Scalar mesons below 1 GeV

Effective range approach to dispersive data analyses

Neural networks applied to the $f_0(980)$

- Continuation of JPAC, PRD 105 (2022) L091501

Takeaways

Standard approach

- **Take an amplitude, it has parameters to be determined by data**
- **Fit data**
- Extract parameters and get pole positions and compute uncertainties
- Assess the probability that those data were generated by your amplitude
- One can do this with different amplitudes that represent different underlying dynamics
- Compare amplitudes? Compare dynamics?

“Data”: S wave from dispersive data analysis $\pi\pi \to \pi\pi, K\overline{K}$

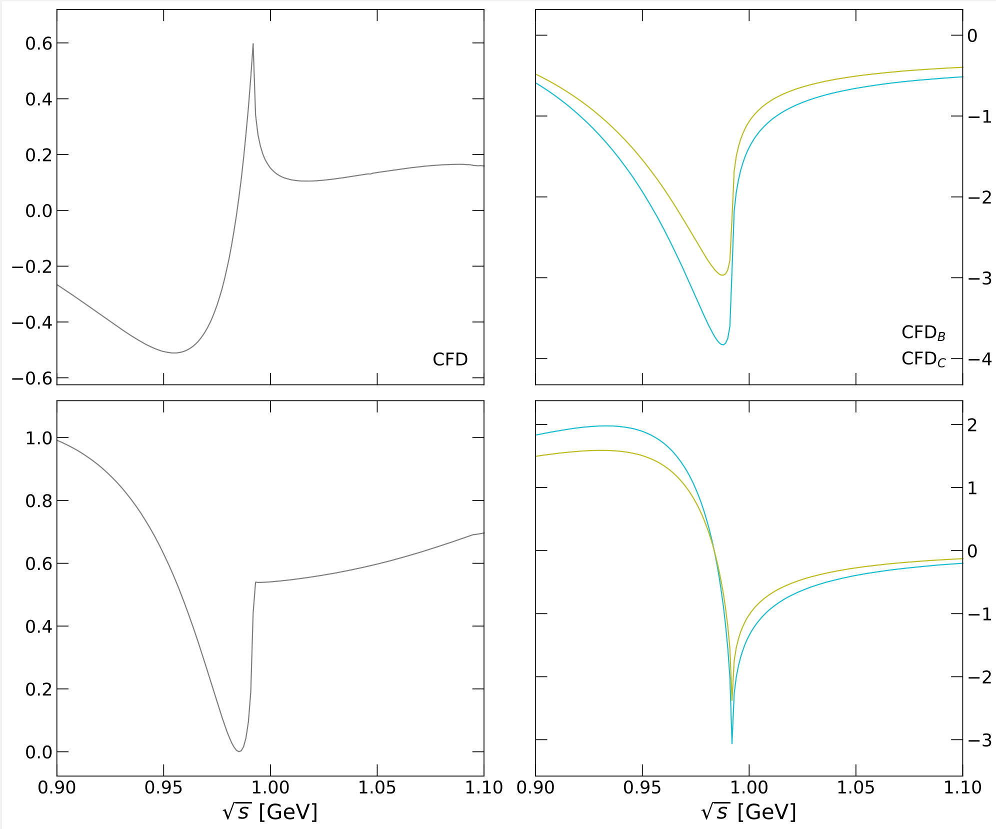
We take the S wave from the dispersive analysis in

(ππ):Garcia-Martin, et al., PRD 83 (2011) 074004
(πK): Peláez, Rodas, Phys.Rept. 969 (2022) 1

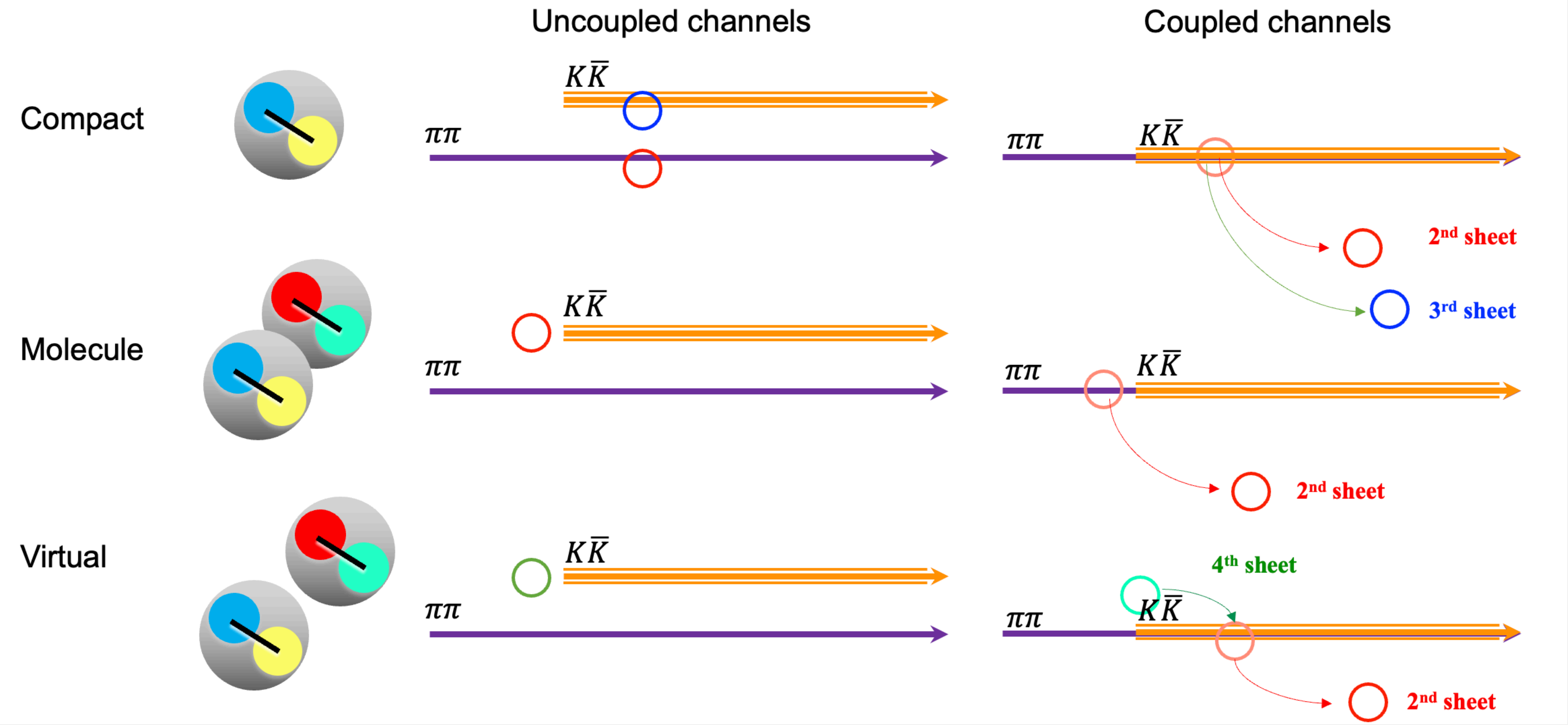
as “data”.

Two solutions base on incompatible datasets for the ππ->KKbar ”data”

B: Longacre *et al.*, PLB 177 (1996) 223
C: Cohen, et al. PRD22 (1980) 2595
Etkin *et al.*, PRD25 (1982) 1786



Interpretation: Morgan-Pennington criterion



Morgan, Pennington, PLB258 (1991) 444

Model: Two-channel effective range

$$S_{ij}(s) = \delta_{ij} + 2i\sqrt{k_i\, k_j}\, T_{ij}(s)$$

$$k_i = \sqrt{s - s_i}$$

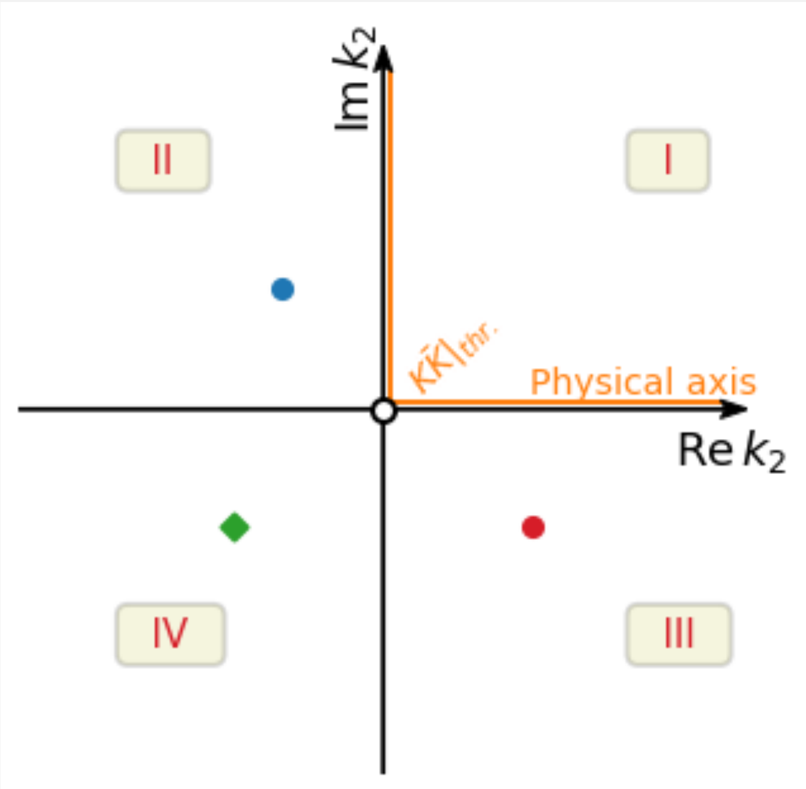
$$T^{-1}_{ij}(s) = M_{ij}(s) - ik_i\, \delta_{ij},$$

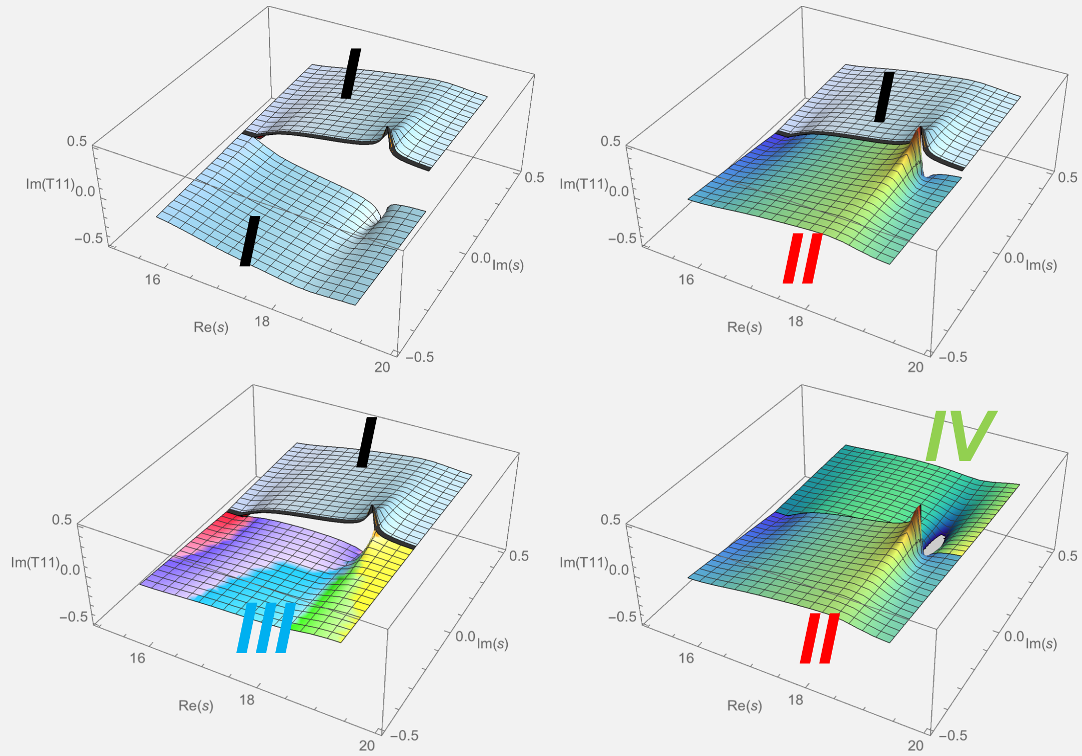
$$M_{ij}(s) = \mu_{ij} - c_{ij} s,$$

See, e.g.

Frazer, Hendry, PR 134 (1964) B1307
JPAC, PRL 123 (2019) 092001

Riemann sheets structure





Uncertainties: Bootstrap

Associate a distribution to each experimental datapoint

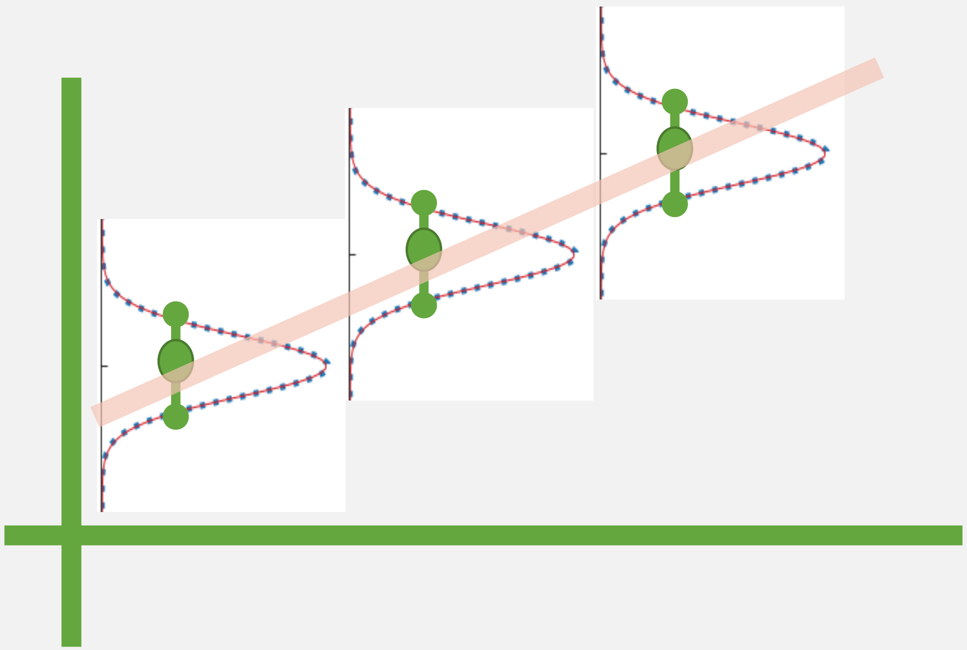
- *Typically a Gaussian with mean and sigma from experiment*

Monte Carlo

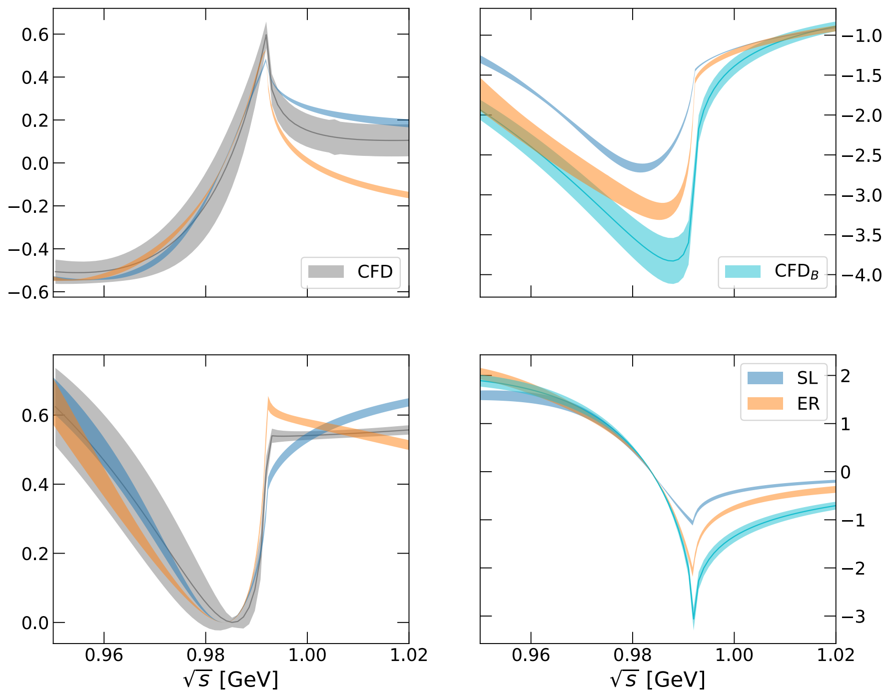
- *Generate pseudodata according to the chosen distribution*

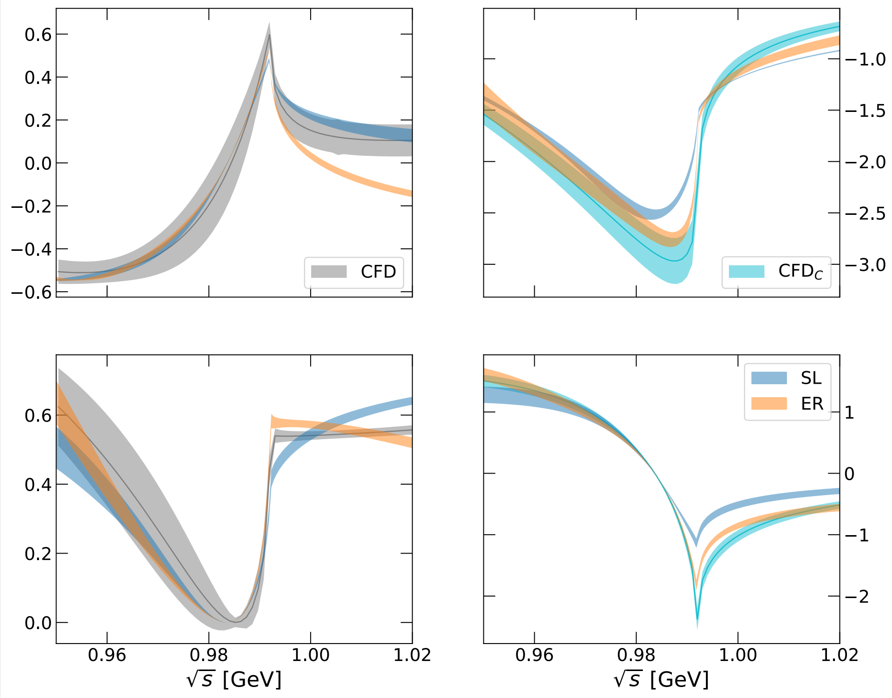
Run statistics on the pseudadtasets

- *Compute distributions, mean, standard deviation, quantiles, …*

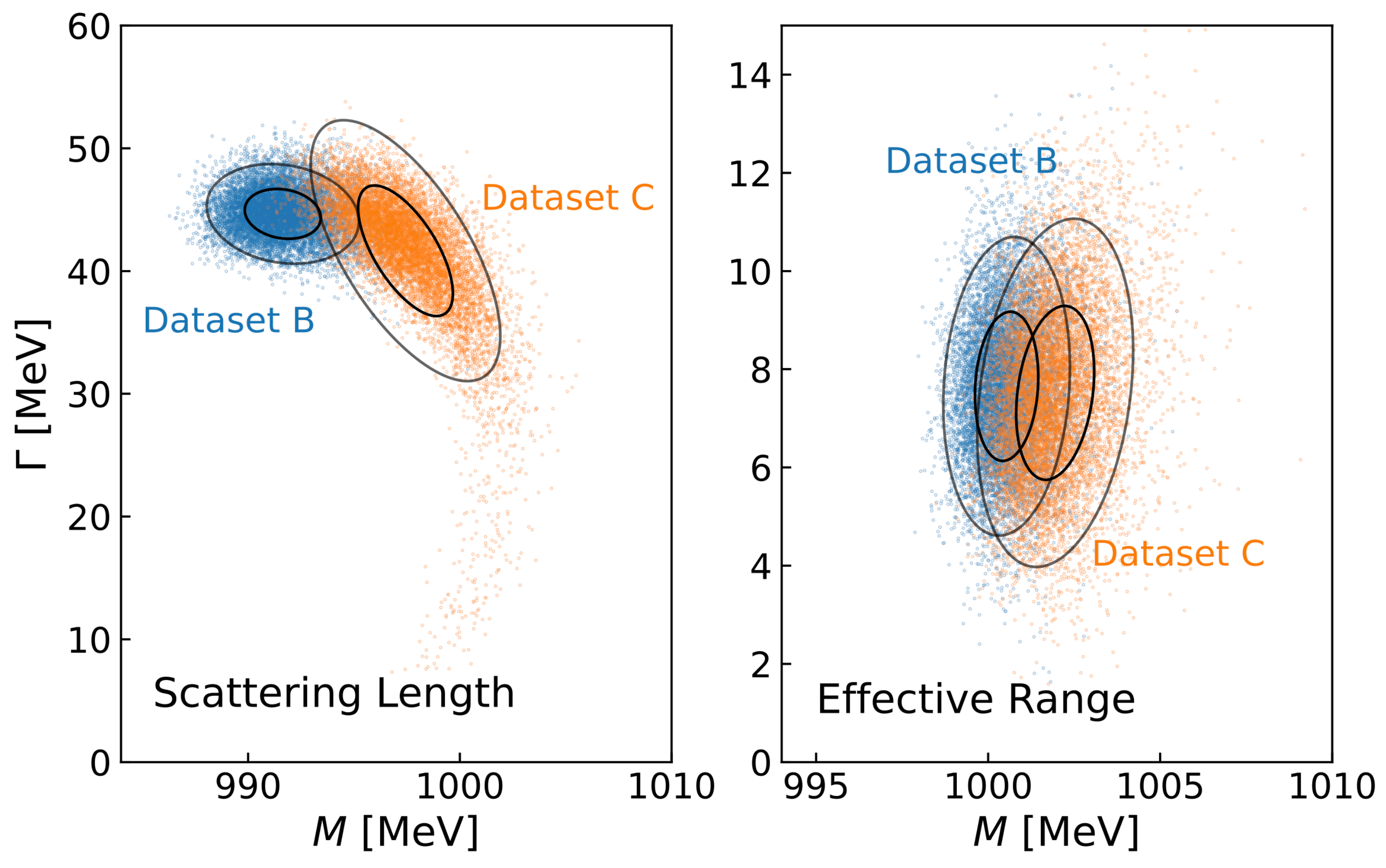


Fit results





Poles



Γ [MeV]
Dataset B
Dataset C
Scattering Length
M [MeV]
Dataset B
Dataset C
Effective Range
M [MeV]

Parameters

TABLE I. Summary of best fits and pole locations (s_p) in the complex s-plane.

Model	dataset B		dataset C	
	Scattering Length	Effective Range	Scattering Length	Effective Range
# params.	3	6	3	6
χ^2/dof	11.7	4.5	6.8	1.8
μ_{11}	0.17(5)	2.9(1.0)	0.0(1)	4.7(6)
μ_{22}	−0.1290(4)	−1.5(2)	−0.1287(3)	−0.8(2)
μ_{12}	−0.379(7)	1.4(2)	−0.398(8)	0.8(1)
c_{11}	–	3.4(1.1)	–	5.2(7)
c_{22}	–	−1.4(2)	–	−0.7(3)
c_{12}	–	1.8(2)	–	1.3(2)
Riemann Sheet	II	II	II	II
$\sqrt{s_p}$ (MeV)	$992(2) - i\,22(1)$	$1000.5(9) - i\,3.8(9)$	$997(2) - i\,21(3)$	$1002(1) - i\,3.8(9)$
$M_p = \mathrm{Re}\sqrt{s_p}$ (MeV)	992(2)	1000.5(9)	997(2)	1002(1)
$\Gamma_p = -2\,\mathrm{Im}\sqrt{s_p}$ (MeV)	45(2)	7.6(1.5)	42(5)	7.5(1.8)

Can machine learning help us?

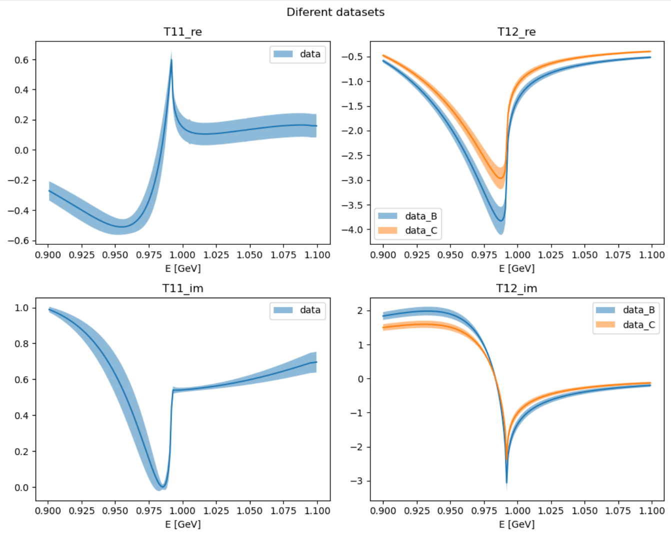
The question

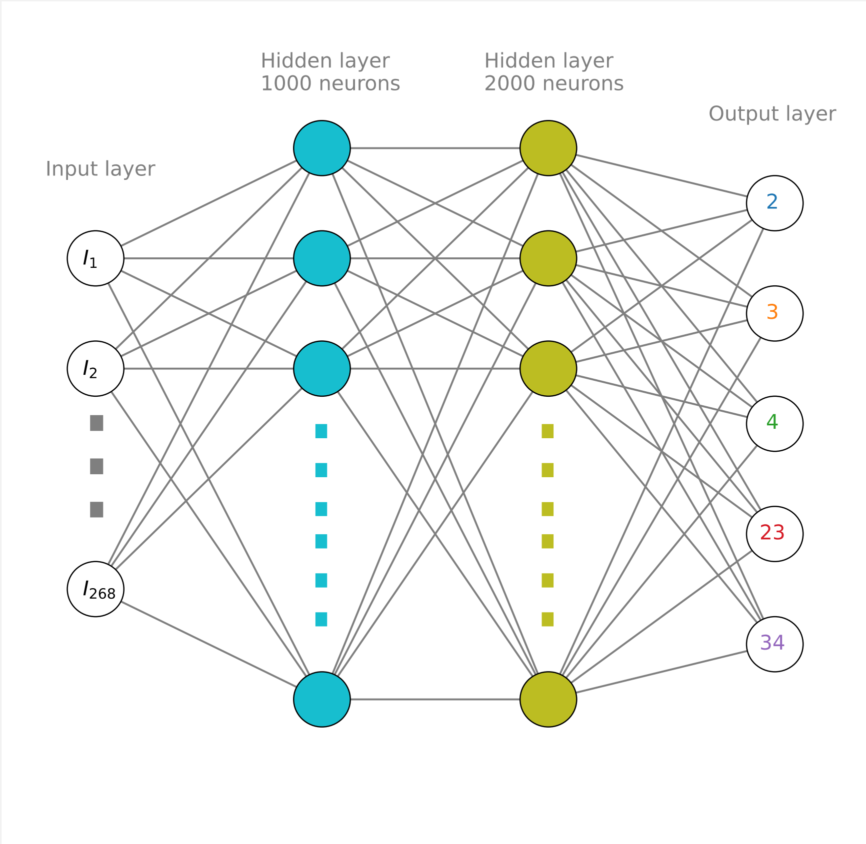
- *Can we train a neural network to analyze a lineshape and get as a result what is the probability of each possible characterization?*

First explorations of neural networks as classifiers for hadron spectroscopy

- Sombillo et al., PRD 102 (2020) 016024, 104 (2021) 036001
- JPAC, PRD 105 (2022) L091501, PPNP 127 (2022) 103981
- Zhang et al. Sci. Bull. (2023), 2301.05364

Holy Grail: ML as a tool for physics discovery

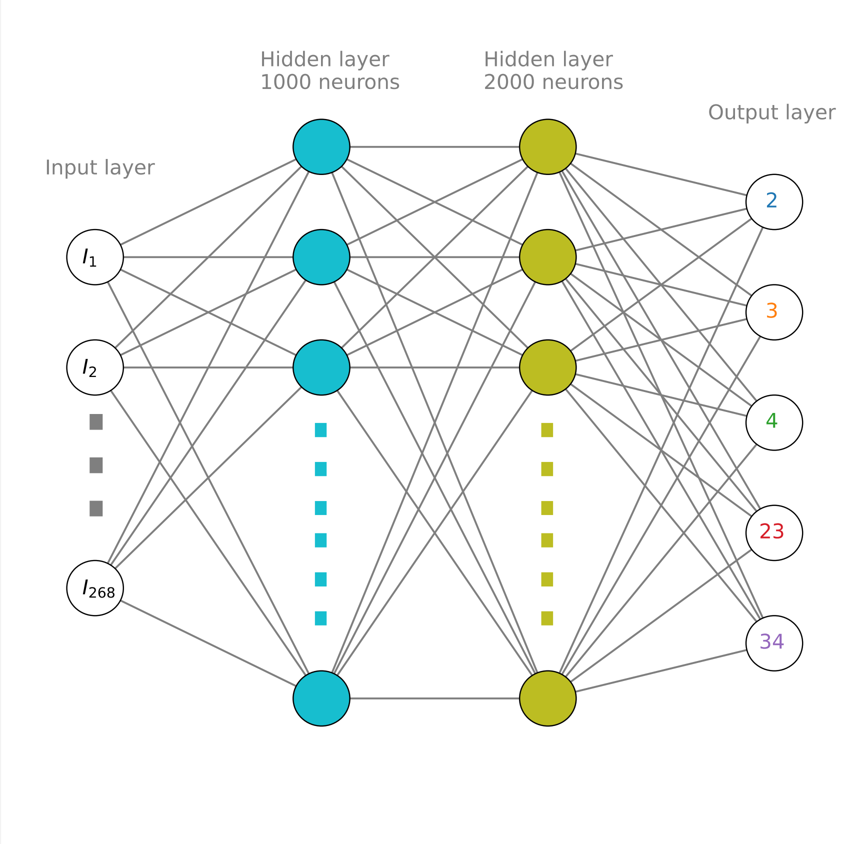




- *Interpretation 1*
- *Interpretation 2*
- *Interpretation 3*
- *Interpretation 4*
- *Interpretation 5*

ML approach

1. **Set the network architecture**
2. Build the training set using the ER model
3. Train the network (there is feedback between points 1, 2, and 3)
4. Put the data through the network and get a result
5. Bootstrap



ML approach

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$$T_{ij}^{-1}(s) = M_{ij}(s) - ik_i\,\delta_{ij},$$

$$M_{ij}(s) = \mu_{ij} - c_{ij}s,$$

Building the training set

10^5 training curves

- *Generated by randomly setting parameter values in a wide range*
- *Curves are computed at the "experimental" energies*
- *Can cleanup unphysical possibilities*

Gaussian noise

- *Included to mimic uncertainties*
- *Compare "blurry" to "blurry"*

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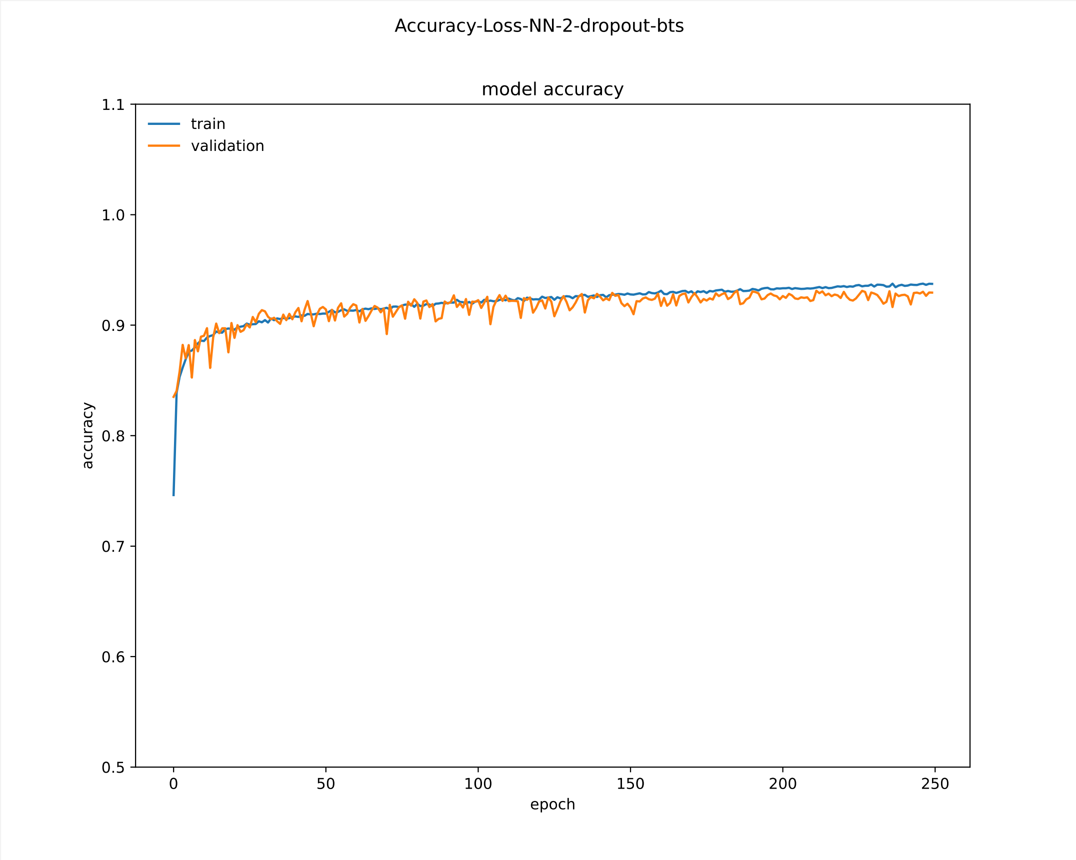

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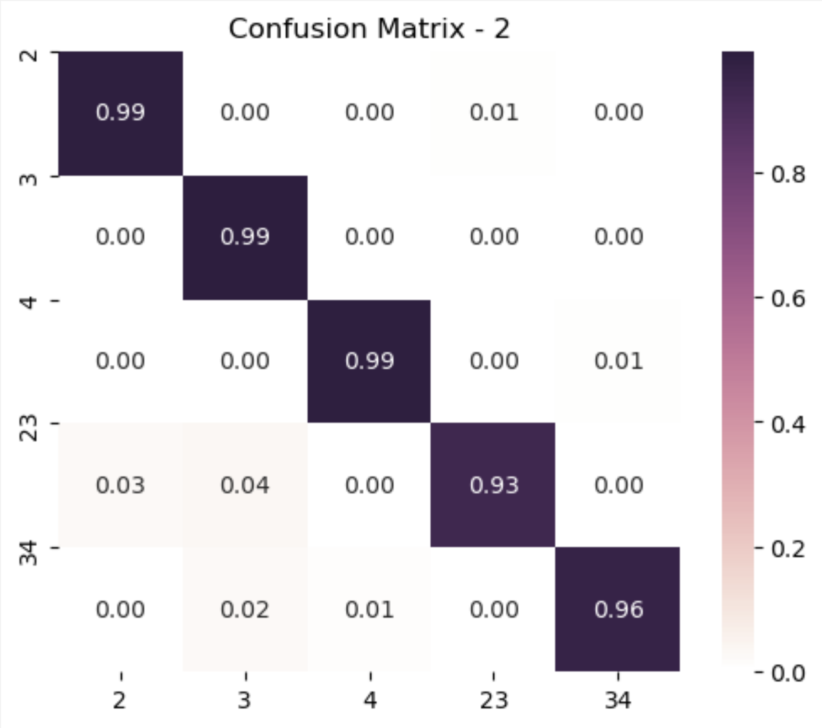

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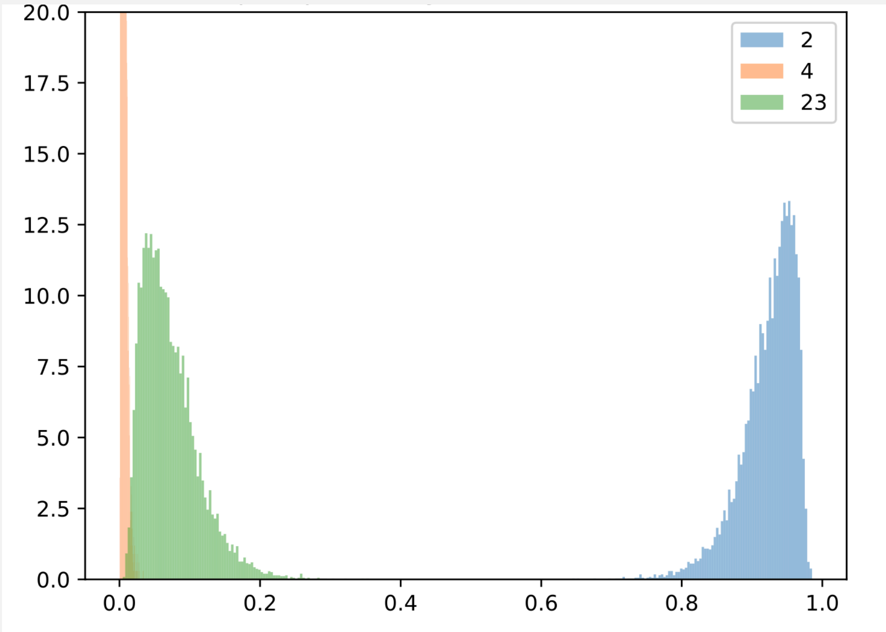

	Class 2	Class 4	Class 23
B	(98.4, 94.7)	(8.3, 0.8)	(27.3, 2.5)
C	(98.5, 91.2)	(3.4, 0.3)	(35.5, 4.7)

Takeaways

- Data support the $f_0(980)$ molecular interpretation
- Towards a data-driven interpretation of resonances
- NN open new possibilities to address the question on the underlying nature of resonances
- NN allows a true comparison among interpretations. Gain physics insight
- NN is not a substitution of the canonical approach to analyzing data