HADRON 2023, Genoa

POLE EXTRACTION AND NATURE OF THE F_0(980)

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with J.A. Silva-Castro, JPAC & EXOHAD
EXOTIC HADRONS TOPICAL COLLABORATION

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 $\pi\pi \to \pi\pi, K\bar{K}$

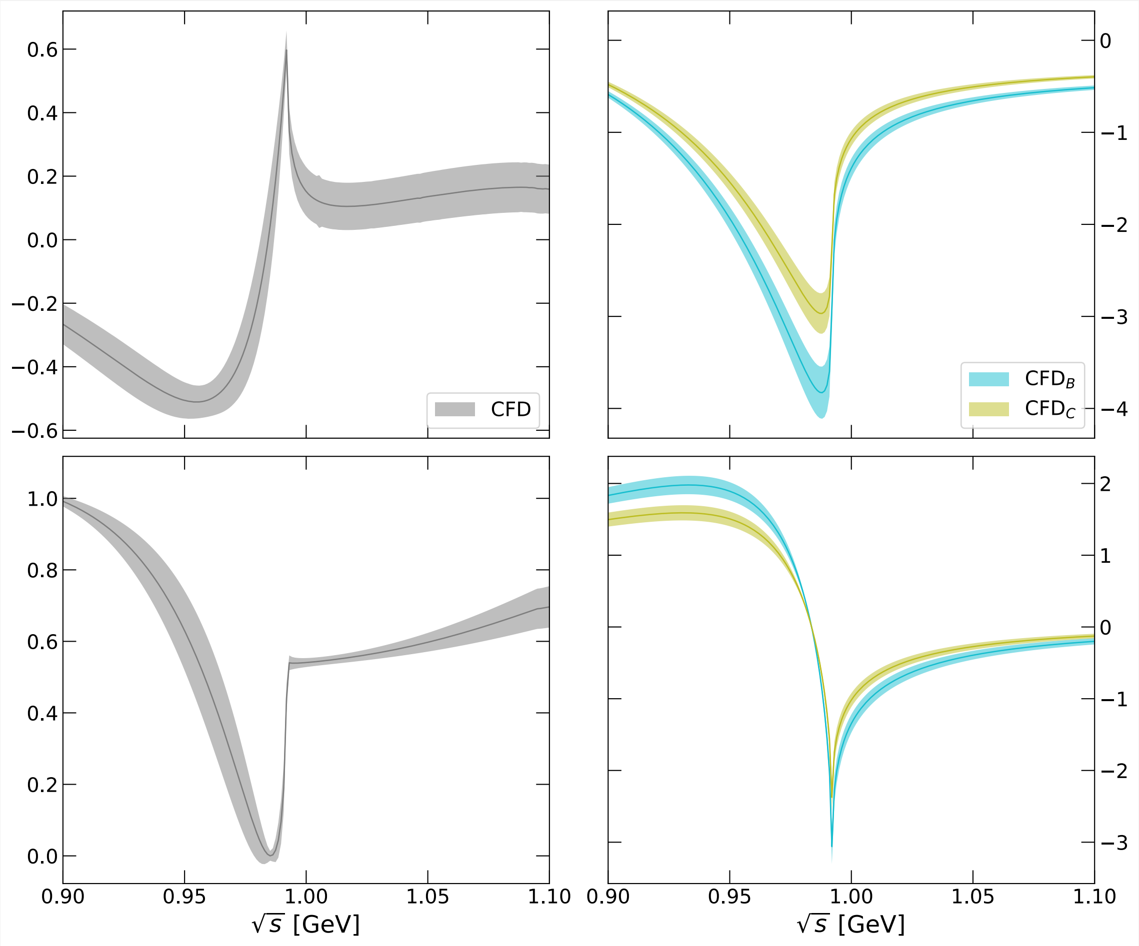
We take the S wave from the dispersive analysis in

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

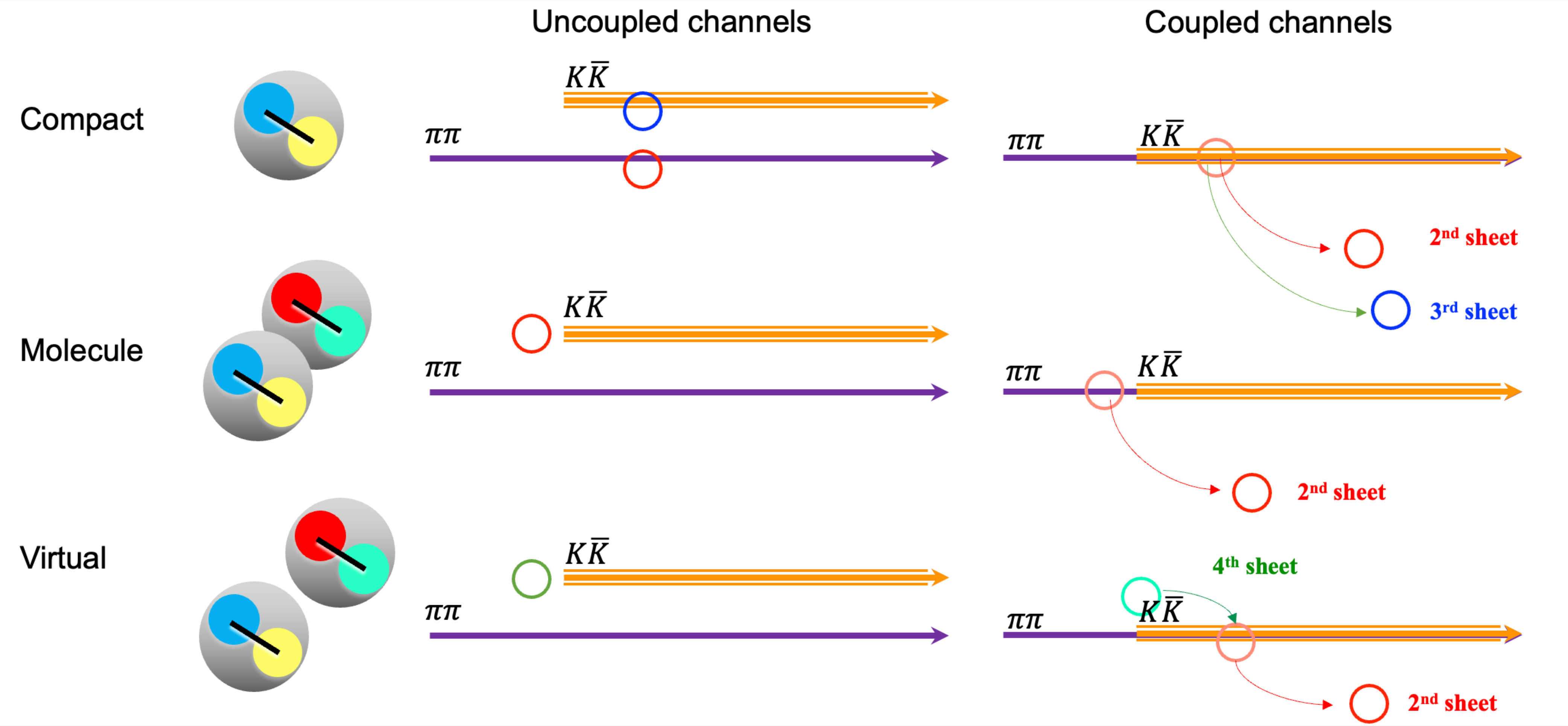
as “data”.

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

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

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

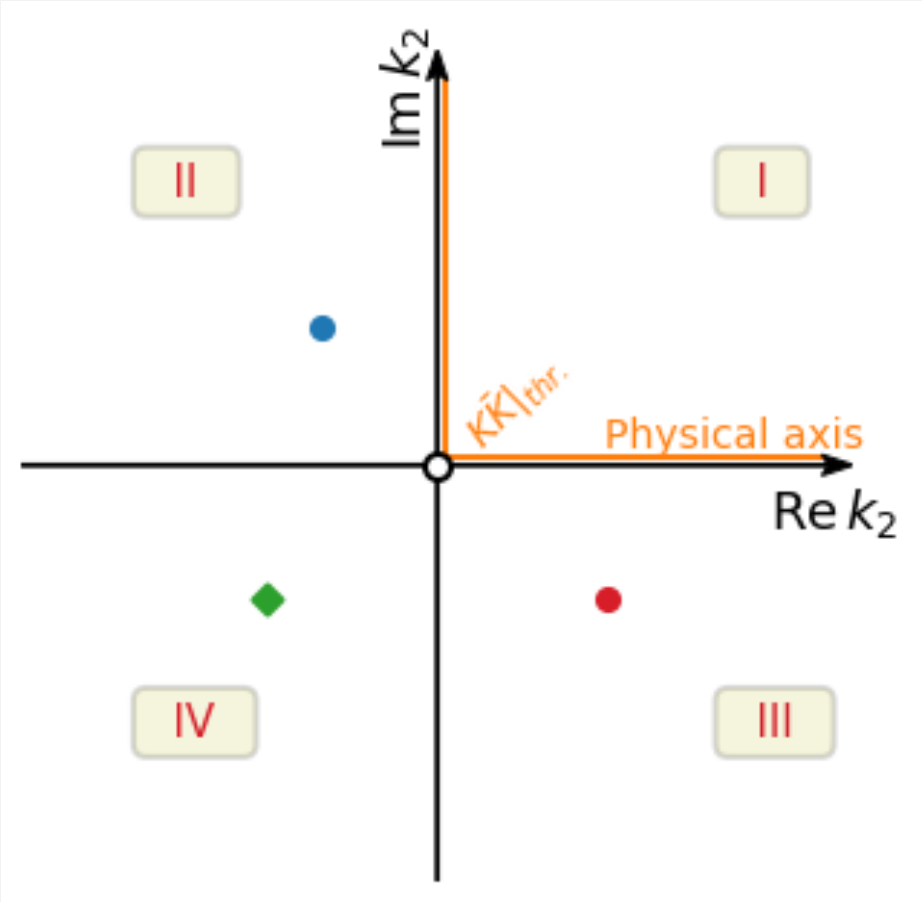
$$T_{ij}^{-1}(s) = M_{ij}(s) - ik_i\, \delta_{ij},$$

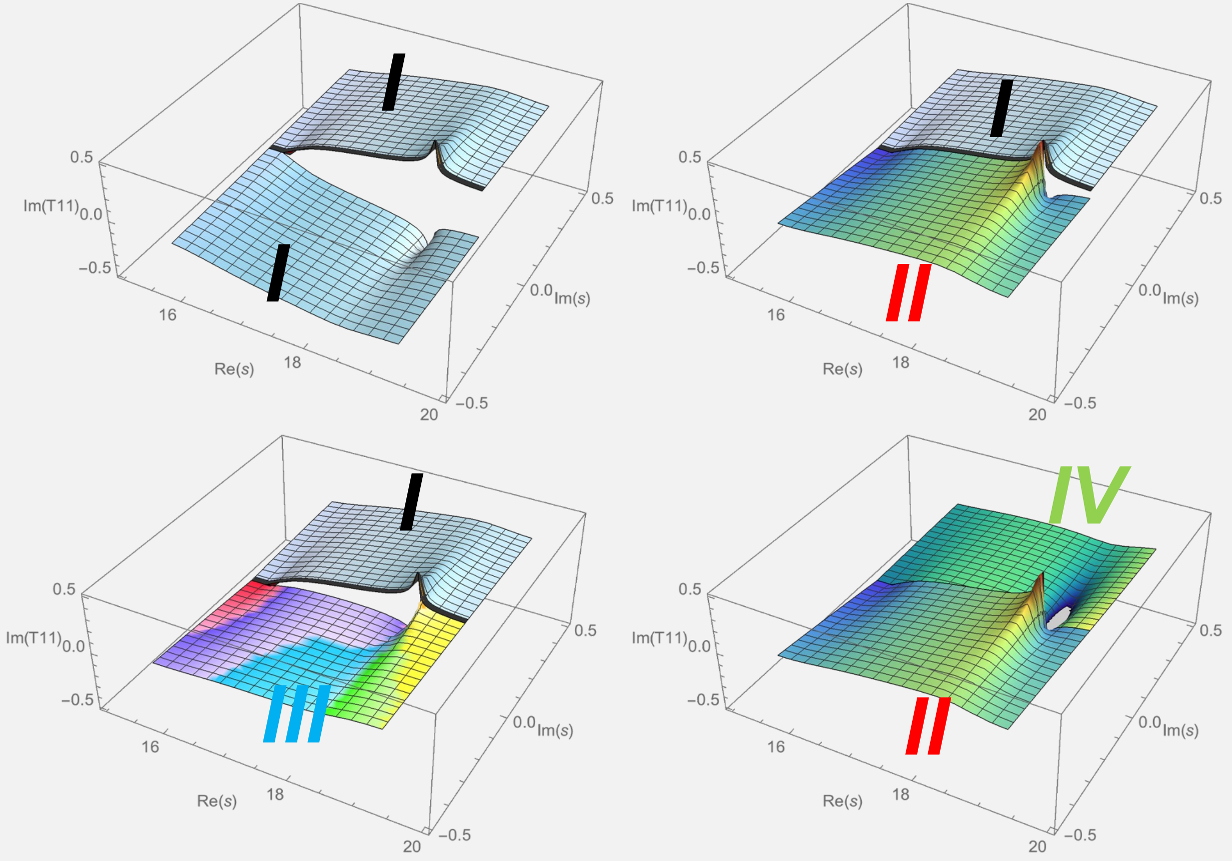
$$M_{ij}(s) = \mu_{ij} - c_{ij} s,$$

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

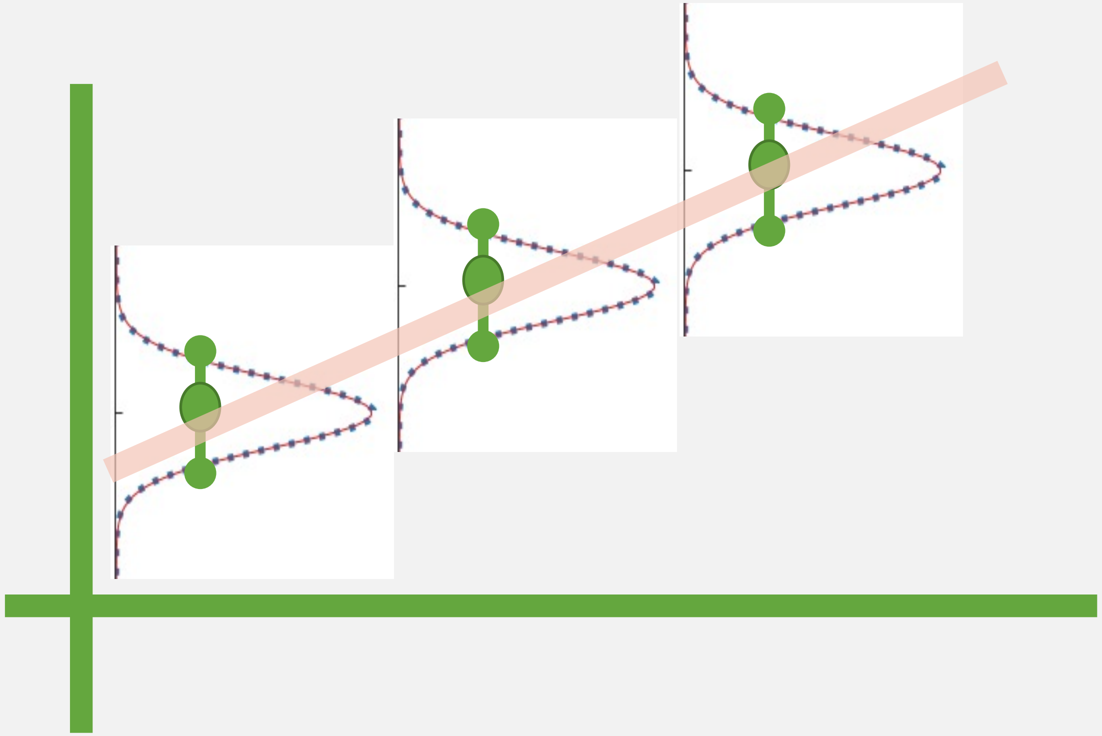
- *Typically a Gaussian with mean and sigma from experiment*

Monte Carlo

- *Generate pseudodata according to the chosen distribution*

Run statistics on the pseudadtasets

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



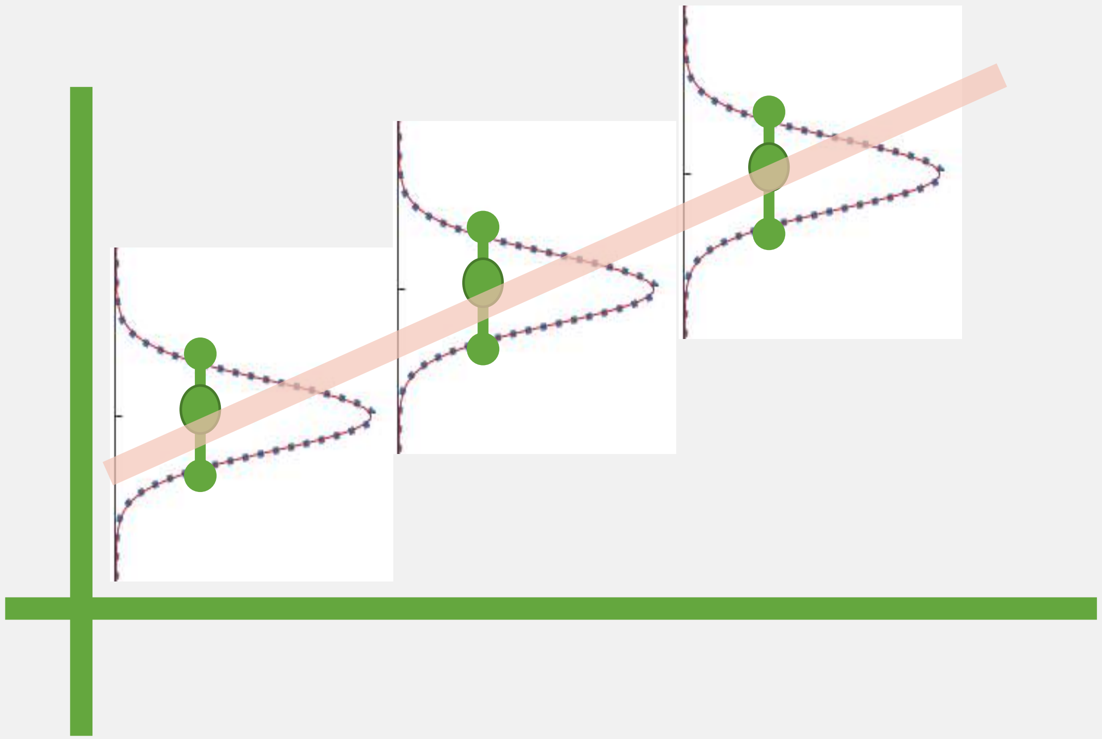
Bootstrap can be "problematic"

Problems

- *Best fit and expected value do not agree*
- *Difficult to assign interpretation as some BS fits have different interpretations*
- *Nearby first Riemann sheet poles might appear*

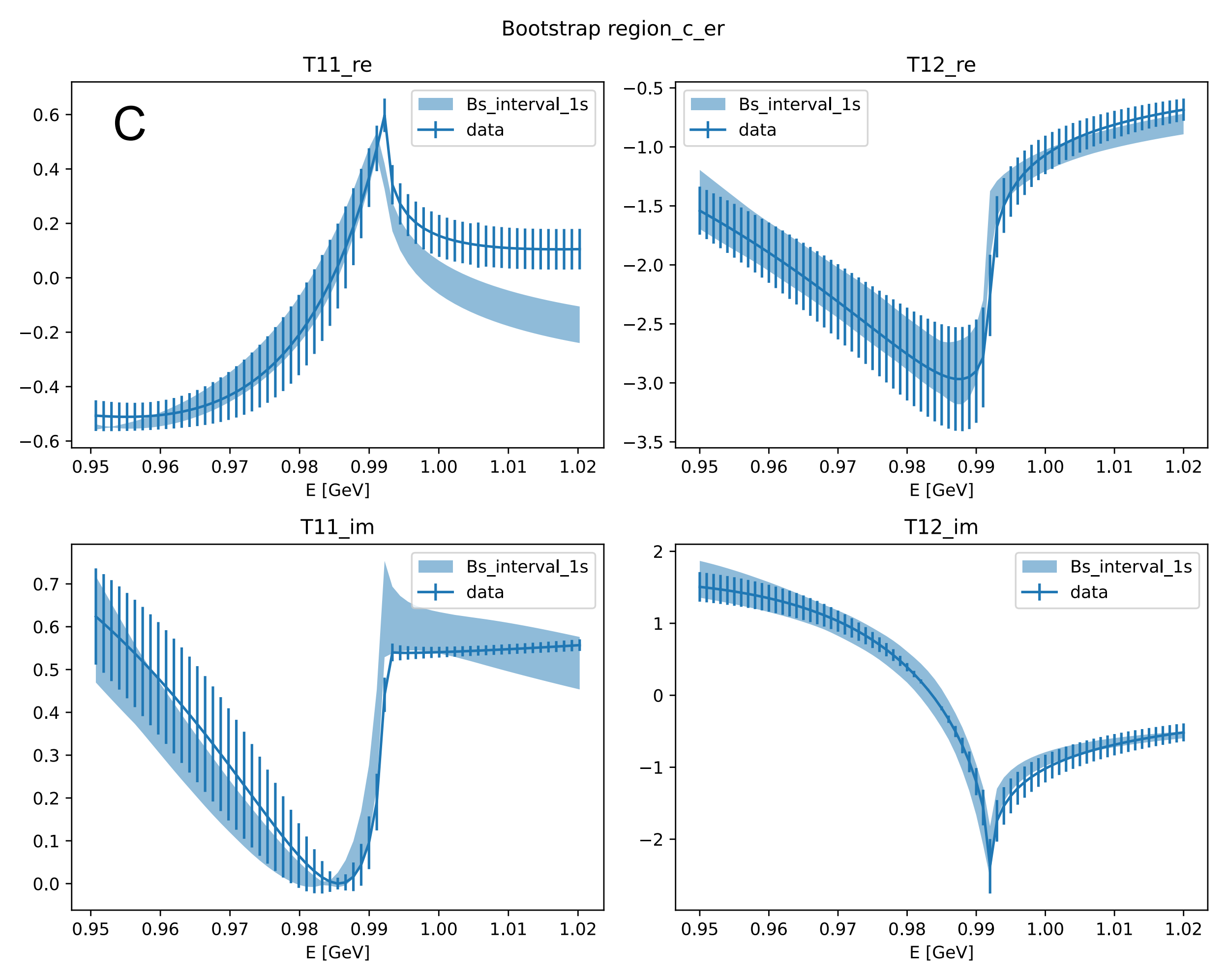
Alternative

- *Generate pseudodata according a shrinked distribution* $\sigma_{new} = {}^{\sigma}/_{\sqrt{N}}$
- *Recalculate errors multiplying by* $\sqrt{N}$
- *Same with pole positions*



Results

	B	C
μ_{11}	6.203(7)	4.482(8)
μ_{22}	$-1.030(1)$	$-0.925(2)$
μ_{12}	0.649(2)	0.8(2)
c_{11}	6.73(2)	5.07(9)
c_{22}	$-0.9243(1)$	$-0.8230(1)$
c_{12}	1.009(4)	1.2(2)
Riemann Sheet	II	II
$\sqrt{s_p}$ (MeV)	$998.4(5) - i\,6.6(4)$	$1000(1) - i\,4.0(8)$
$M_p = \mathrm{Re}\sqrt{s_p}$ (MeV)	998.4(5)	1000(1)
$\Gamma_p = -2\,\mathrm{Im}\sqrt{s_p}$ (MeV)	13.1(8)	8(2)



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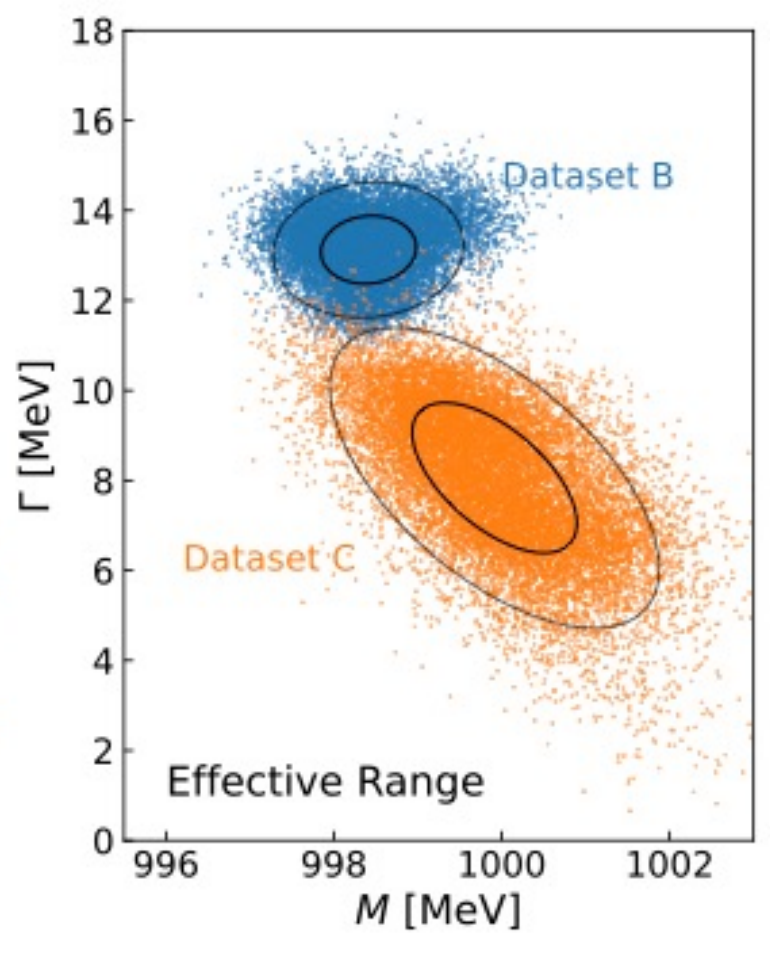


Can machine learning help us?

The question

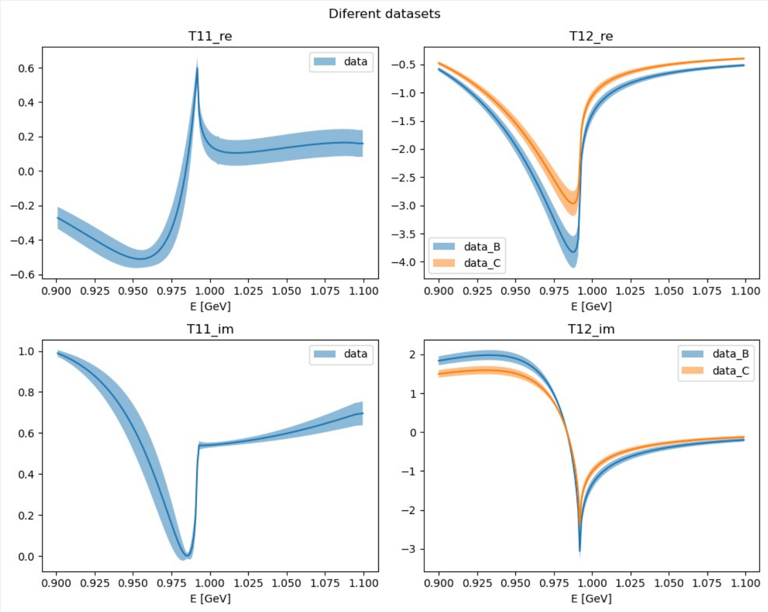
- *Can we train a neural network to analyze a lineshape and get as a result what is the probability of each possible characterization?*

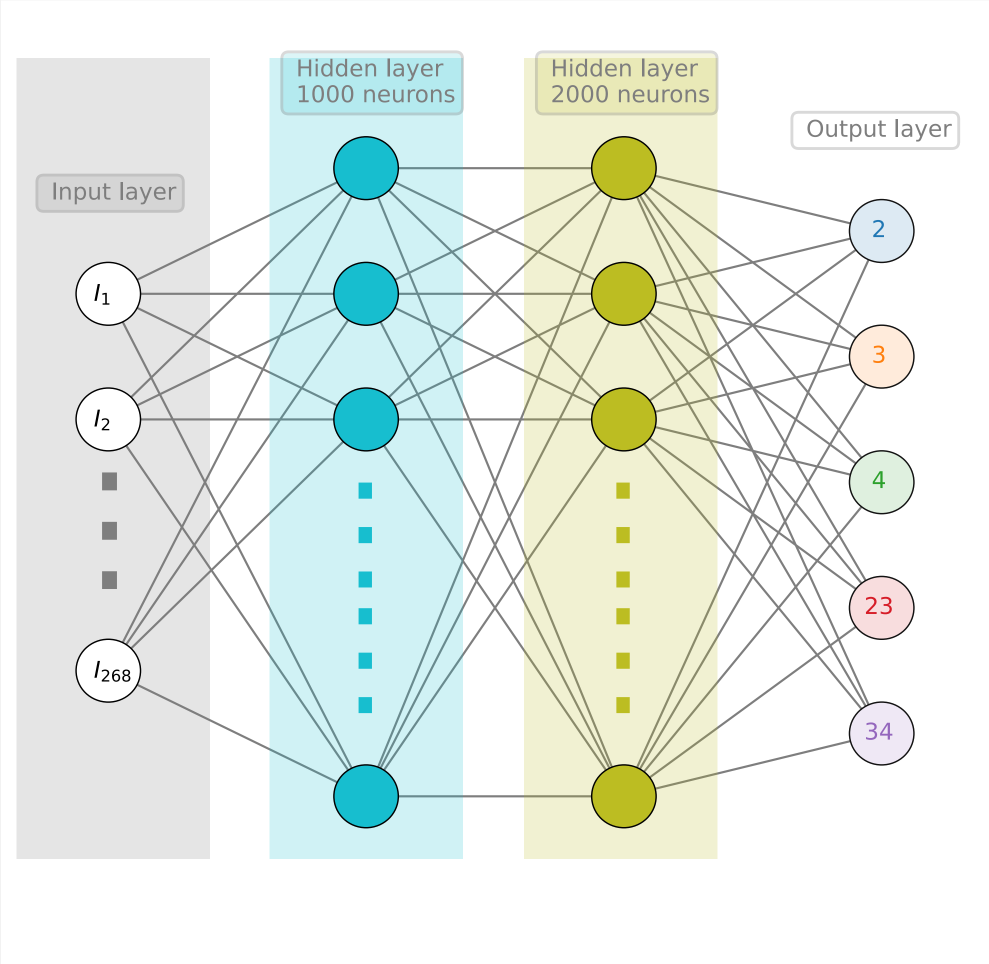
First explorations of neural networks as classifiers for hadron spectroscopy

- 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

Bibrzycki's talk, Analysis Tools track, Room Benvenuto, Thursday@17:25

Holy Grail: ML as a tool for physics discovery

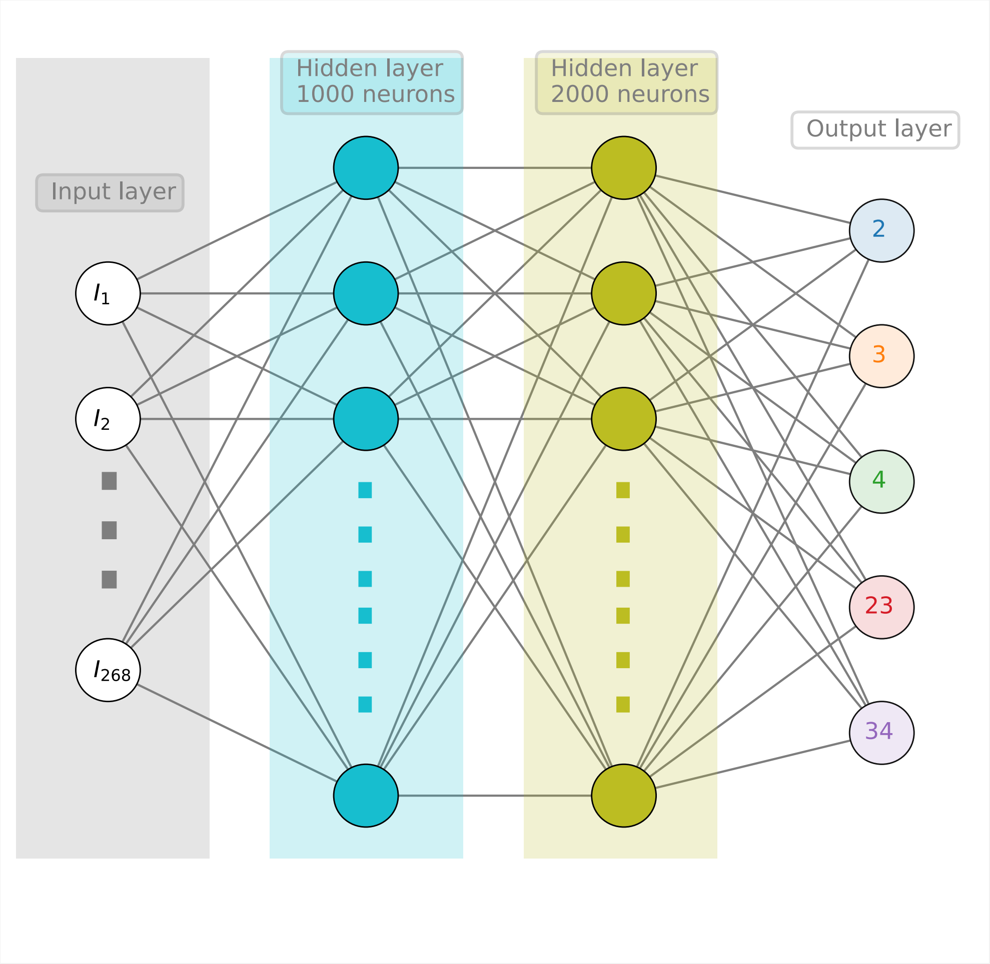




- *Interpretation 1*
- *Interpretation 2*
- *Interpretation 3*
- *Interpretation 4*
- *Interpretation 5*

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

1. Set the network structure
2. **Build the training set using the ER model**
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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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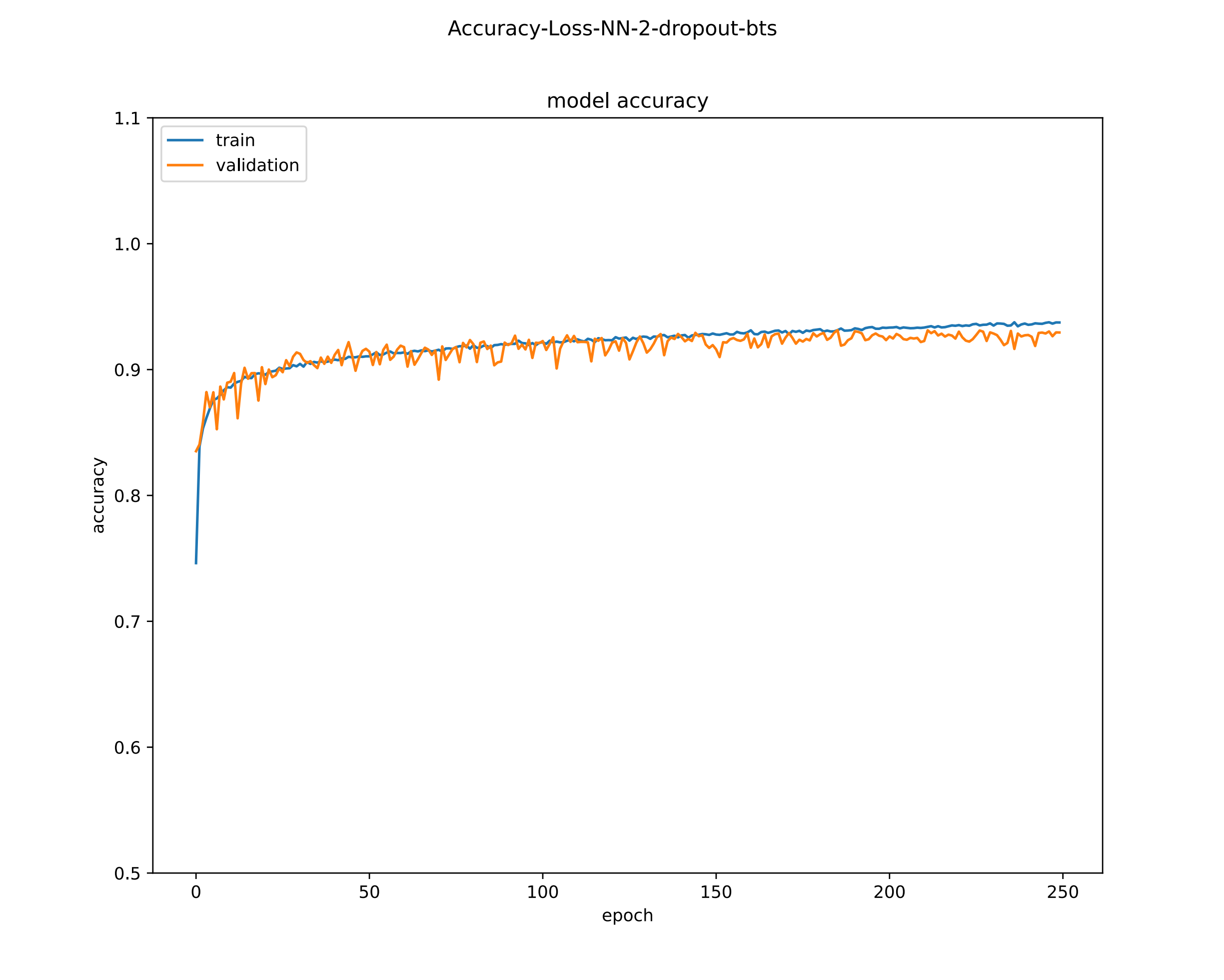

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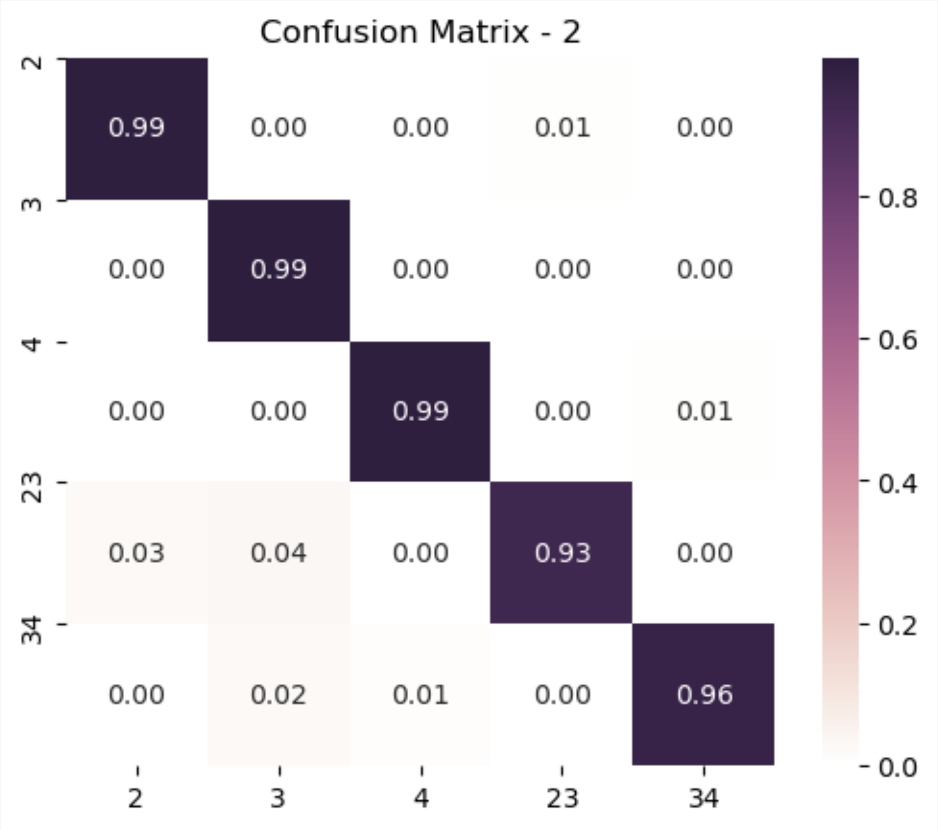

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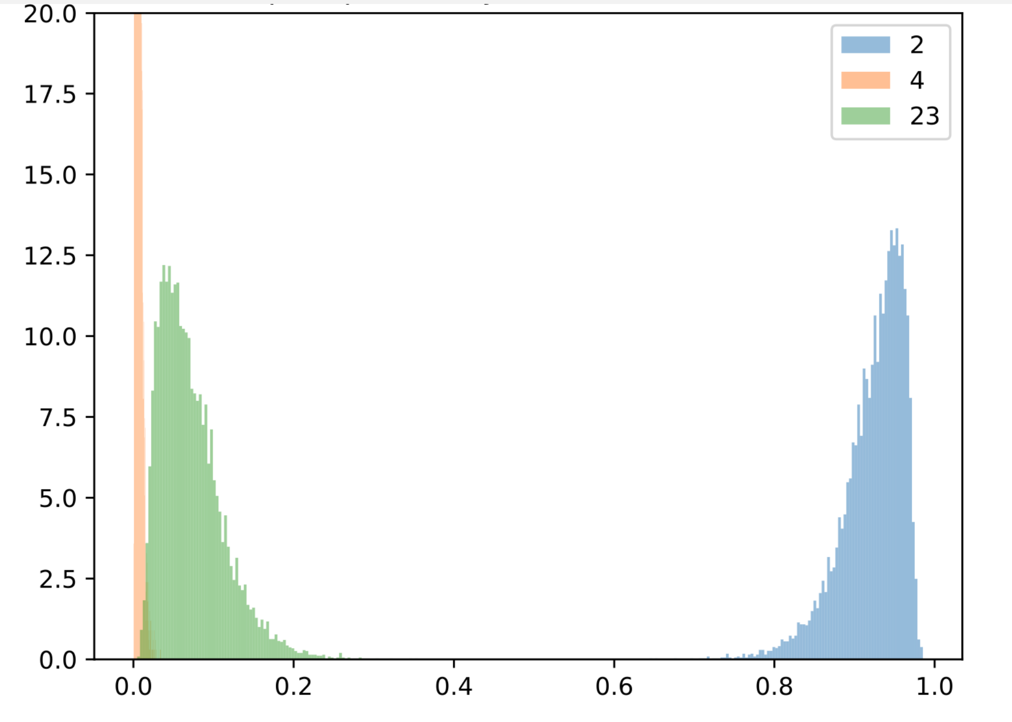

	Class 2	Class 4	Class 23
B	(98.4, 94.7)	(8.3, 0.8)	(27.3, 2.5)
C	(98.5, 91.2)	(3.4, 0.3)	(35.5, 4.7)

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