

BARYONS AS SOLITONS IN THE MESON SPECTRUM: A MACHINE LEARNING PERSPECTIVE

Damián K. Mayorga Peña

arXiv:2003.10445

In collaboration with Yarin Gal, Vishnu Jejjala and Challenger Mishra.



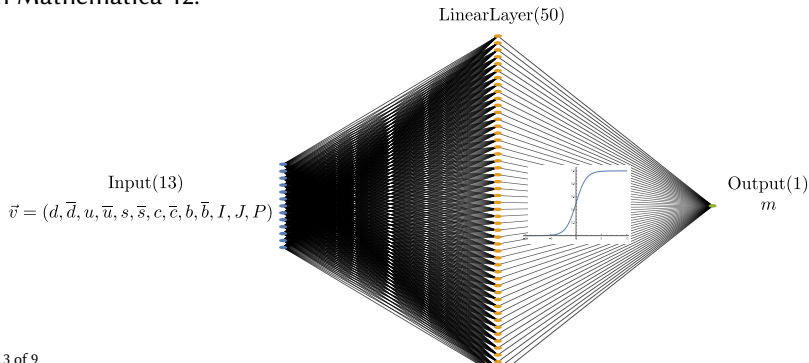
String Data 2020

Introduction & Motivation

- QCD is the theory of strong interactions and has quarks and gluons as fundamental particles. Being non perturbative at low energies it forms colorless bound states at low energies (hadrons), among which, mesons and baryons are of primary interest.
 - Computing such resonances is relatively involved. Many phenomenological models were developed for that purpose with relative success, e.g. the quark model, the soliton Skyrme model, lattice QCD.
 - Early observations lead to the fact that in the large N limit, mesons become free and non interacting while baryon resonances behave as solitonic objects. In that limit mesonic data should suffice to know the baryon spectrum.
- 't Hooft'74, Witten'79;...
- $N = 3$ is large enough! Mesons are mainly $q\bar{q}$ states and can be distinguished from tetraquark states, etc. Also AdS/CFT has been used to describe certain features of the quark gluon plasma.
 - Our aim is to use the information on the meson spectrum of QCD to be able to predict baryonic data. We make use of two techniques: Artificial Neural Networks and Gaussian Processes.

ANN Approach

We want to train on the mesonic data from the PDG (composition, isospin, angular momentum, parity) to get the meson mass as an output. After trying on various architectures, we find a single layer ANN that is well suited for our problem. We train with 80% and 100% of the mesonic data. Implementation on Mathematica 12.



GP Approach

For the Gaussian process we first specify a positive definite *kernel*

$$K_{ij} := k(x_i, x_j) ,$$

where $i = 1, \dots, M$ runs over the set of training data (mesons). The *covariance* function defines the prior on noisy observations:

$$\text{cov}(x_i, x_j) = k(x_i, x_j) + N_{i,j} , \quad \text{where } N_{i,j} = \sigma_n^2 \delta_{i,j} .$$

For our problem we take the kernel to be rational quadratic

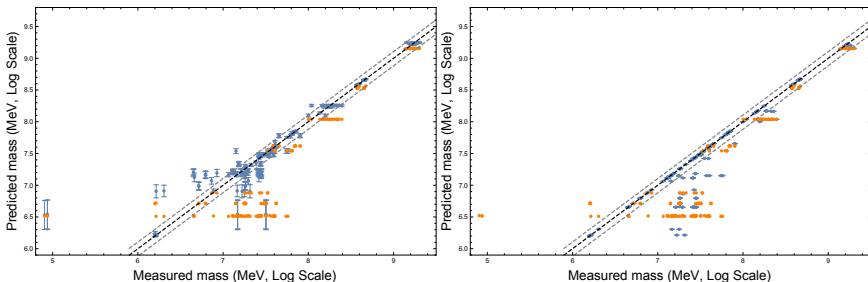
$$k_{\text{RQ}}(x_i, x_j) = \sigma_f^2 \left(1 + \frac{1}{2\alpha} (x_i - x_j)^\top \Lambda^{-1} (x_i - x_j) \right)^{-\alpha} ,$$

where $\Lambda = \text{diag}(\lambda_i^2)$, ($i = 1, \dots, D$). Model selection in GP is done by maximizing the *log marginal likelihood* with respect to a training set $\{x_i \rightarrow y_i\}_{i=1}^M$. Implemented with GPML 4.2 in Matlab R2019b

$$\log p(y|X) := -\frac{1}{2} y^\top (K + N)^{-1} y - \frac{1}{2} \log |K + N| - \frac{M}{2} \log(2\pi) ,$$

Fitting the mesonic data

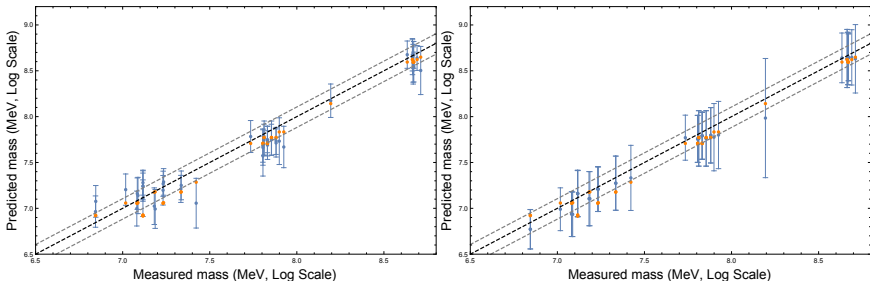
Training with 100% of the mesonic data we obtain the following predictions for the mesonic masses. For the composition of mesons we took the Monte Carlo numbering of PDG. ANN left, GP right.



Errors in the meson sector: ANN 18.5% , GP 13.3%, CQM 39.3%.

Predictions for baryons

Training with 100% of the mesonic data we obtain the following predictions for the mesonic masses. ANN left, GP right.



Errors in the meson sector: ANN 9.7%, GP 3.4%. CQM 8.6%. Consistent with expectation for errors of order $1/N^2 \sim 10\%$.

Predictions for baryons

Probabilities for different baryons to be the lightest particles in the spectrum according to the ANN predictions.

	p	n	Λ^0	Σ^+	Σ^0	Σ^-	Δ^{++}
#1	79.0	2.0	0.0	4.6	0.0	2.5	5.3
#2	13.9	26.7	0.0	12.5	1.2	5.5	22.5
#3	4.5	21.7	0.3	15.9	2.2	8.6	14.7
#4	1.9	14.7	0.6	17.3	5.7	8.5	13.6
#5	0.6	11.1	2.3	15.6	6.2	11.8	9.2
#6	0.1	9.1	3.9	9.6	8.0	10.7	5.8
#7	0.0	4.8	6.7	7.9	11.0	9.8	5.6

Predictions:

$$\text{ANN: } m_p = 1068 \pm 183 \text{ MeV}, \quad m_n = 1205 \pm 206 \text{ MeV}$$

$$\text{GP: } m_p = 893 \pm 194 \text{ MeV}, \quad m_n = 892 \pm 193 \text{ MeV}$$

$$m_p = 938.28 \text{ MeV} \quad m_n = 939.57 \text{ MeV}$$

Predictions for pentaquarks

- The $\Theta(1540)^+$ with composition $uudd\bar{s}$, was predicted by many phenomenological models, its most likely quantum numbers are $I(J^P) = 0(\frac{1}{2}^+)$. The mass predicted by the NN is

$$m_{\Theta(1540)^+} = 1564 \pm 62 \text{ MeV},$$

- For the molecular pentaquarks $P_c(4380)^+$ and $P_c(4450)^+$ with composition $uudc\bar{c}$ recently discovered at LHCb, we obtain the NN prediction

	$I(J^P)$	ANN prediction (MeV)	GP prediction (MeV)
$P_c(4380)^+$	$\frac{1}{2}(\frac{3}{2}^-)$	$(4.1 \pm 1.1) \cdot 10^3$	3253 ± 846
$P_c(4450)^+$	$\frac{1}{2}(\frac{5}{2}^+)$	$(4.5 \pm 1.1) \cdot 10^3$	3581 ± 932

Summary and Prospects

- We would like to find a simple equation for baryon and proton masses (in the spirit of the Gell-Mann Okubo formula). GPs give a closed but complicated expression with 17 adjusted parameters. For the ANN it is crucial to identify the relevant components. Techniques such as Principal Component Analysis could be helpful to determine the relevant contributions from the various inputs.
- We have not trained the ANN and GP to distinguish matter from antimatter. Predictions for antibaryons differ by at most 6% from their baryon counterparts.
- Our algorithms use only quark information. It would be appealing if we could add additional gluon information. This could help to make predictions on exotic states such as glueballs.

Summary and Prospects

- We would like to find a simple equation for baryon and proton masses (in the spirit of the Gell-Mann Okubo formula). GPs give a closed but complicated expression with 17 adjusted parameters. For the ANN it is crucial to identify the relevant components. Techniques such as Principal Component Analysis could be helpful to determine the relevant contributions from the various inputs.
- We have not trained the ANN and GP to distinguish matter from antimatter. Predictions for antibaryons differ by at most 6% from their baryon counterparts.
- Our algorithms use only quark information. It would be appealing if we could add additional gluon information. This could help to make predictions on exotic states such as glueballs.

Thanks!