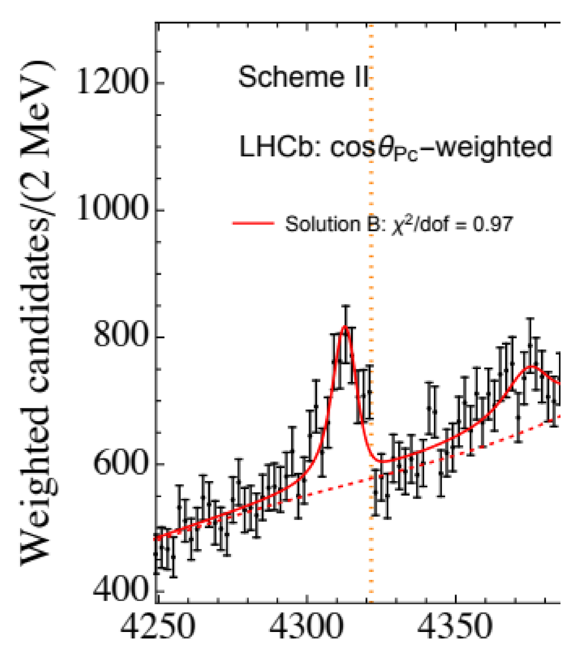
Classification of hadron candidates with Machine Learning

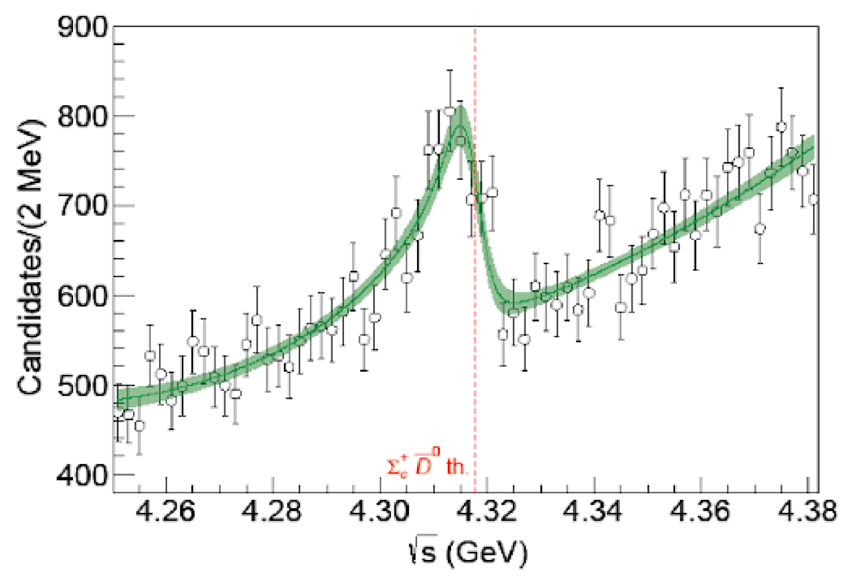
Łukasz Bibrzycki* and Marcin Piekarczyk (on behalf of the JPAC collaboration)
Institute of Computer Science, Pedagogical University of Krakow, Podchorążych 2, 30-084 Kraków, Poland
lukasz.bibrzycki@up.krakow.pl

1. Motivation

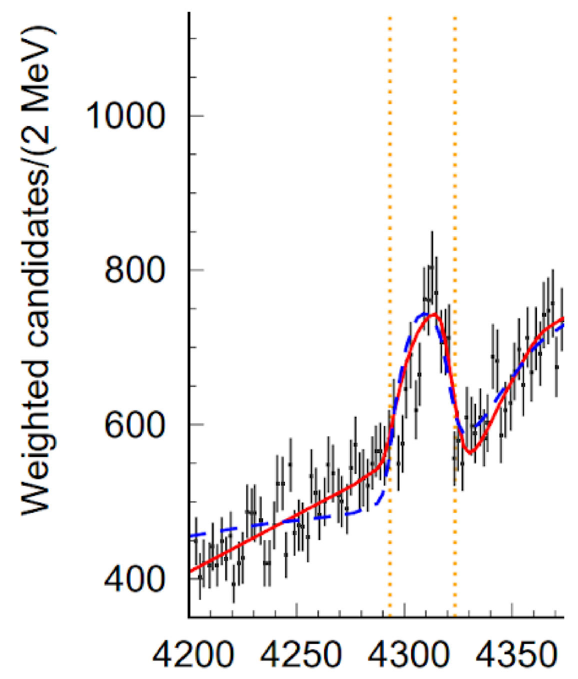
- Throughout the last two decades we have witnessed a plethora of exotic particle observations both in the meson and baryon sectors. Theorists have put forward the interpretations in terms of tetraquarks, pentaquarks, molecules and hybrids. These interpretations are often contradictory, eg.



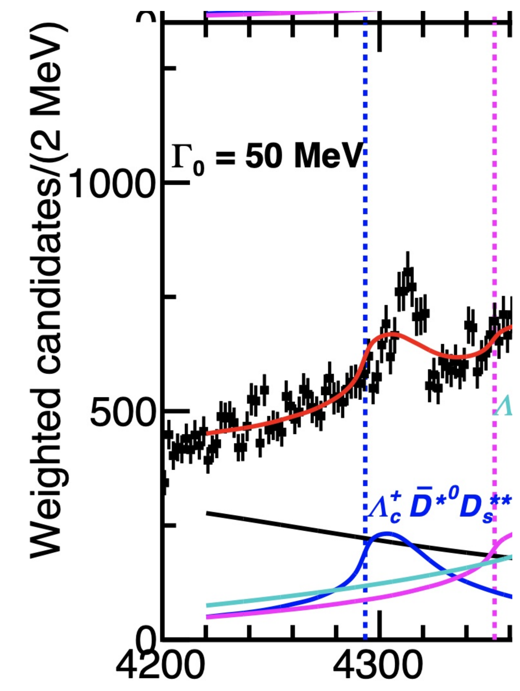
Molecule
Du et al., JHEP 08, 157 (2021)



Virtual
Ramirez et al. (JPAC), Phys. Rev. Lett. 123, (2019)



Double triangle
Nakamura, Phys. Rev. D 103, 111503 (2021)

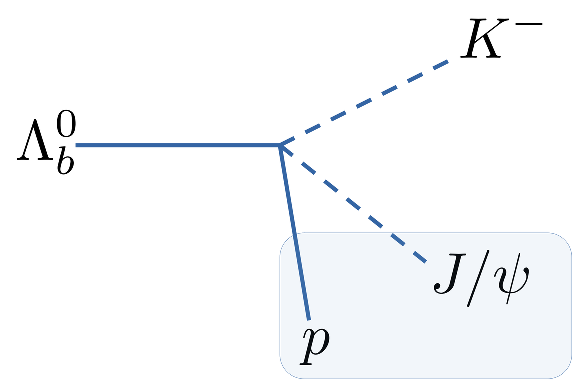


Single triangle
LHCb, Phys. Rev. Lett. 122, 222001 (2019)

- Our objective is to unambiguously identify the type of singularity that describes the pJ/ψ-energy dependent intensity $dN/d\sqrt{s}$.
- We show that the Artificial Neural Network provides the means to assess the probability of various possible dynamical explanations.

2. Physical model

- We study the resonance observed in the pJ/ψ system at the energy around 4.32 GeV.
- At this energy the $\Sigma_c^+\bar{D}^0$ channel is opened, so we handle the 2-channel problem



- Energy dependent intensity is defined as [1]:

$$\frac{dN}{d\sqrt{s}} = \rho(s)\left[|P_1(s)T_{11}(s)|^2 + B(s)\right], \qquad (1)$$

where $\rho(s) = pqm_{\Lambda_b}$ is the phase space factor with $p = \lambda^{\frac{1}{2}}(s, m_{\Lambda_b}^2, m_K^2)/2m_{\Lambda_b}$ and $q = \lambda^{\frac{1}{2}}(s, m_p^2, m_\psi^2)/2\sqrt{s}$.

- The elastic pJ/ψ scattering amplitude in the scattering length approximation reads

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

where k_i are channel momenta and $P_1(s)$ and $B(s)$ parametrize the production amplitude and background, respectively.

$$P_1(s) = p_0 + p_1 s, \quad B(s) = b_0 + b_1 s \qquad (3)$$

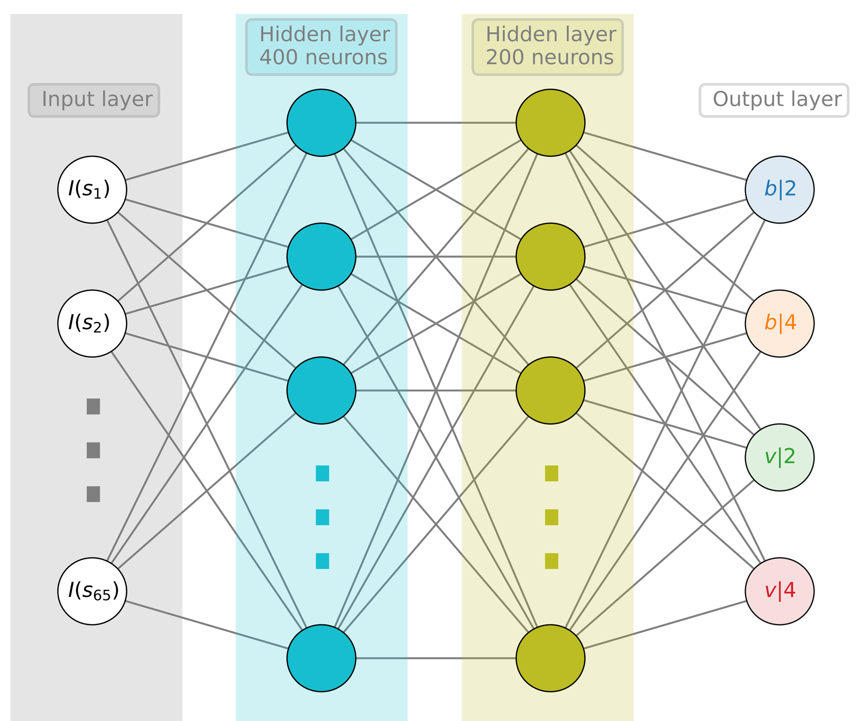
3. Training data set

The ANN is trained to predict one of the four classes defined by the combination of

- the location of two poles on either the 2nd or 4th Riemann sheet (two poles on other sheets are far away from the physical region) and
- the location of poles in the uncoupled model that corresponds to bound or virtual state. This property is controlled by the m_{22} parameter of the amplitude

The training data set of $2 \cdot 10^5$ samples is produced by computing intensity from Eq.(1) with randomly sampled parameters p_0, p_1, b_0, b_1, m_{11}, m_{22} and m_{12}^2.

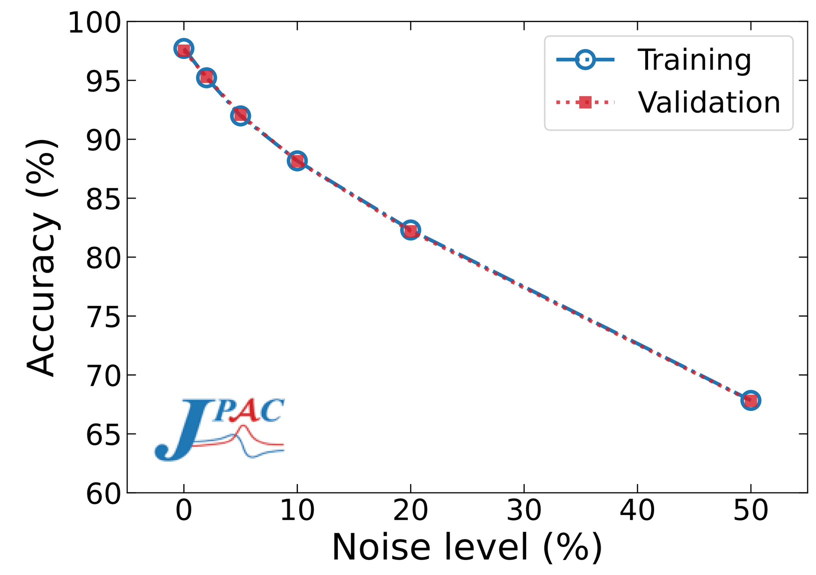
4. ANN architecture and training



Intensities are split into 65 energy bins with the 5% Gaussian noise added to mimic the experimental uncertainty. Then the signal is fed to the ANN and matched with one of the four classes:

- b|2 (bound state, 2nd Riemann sheet),
- b|4 (bound state, 4th Riemann sheet),
- v|2 (virtual state, 2nd Riemann sheet),
- v|4 (virtual state, 4th Riemann sheet).

5. ANN model validation

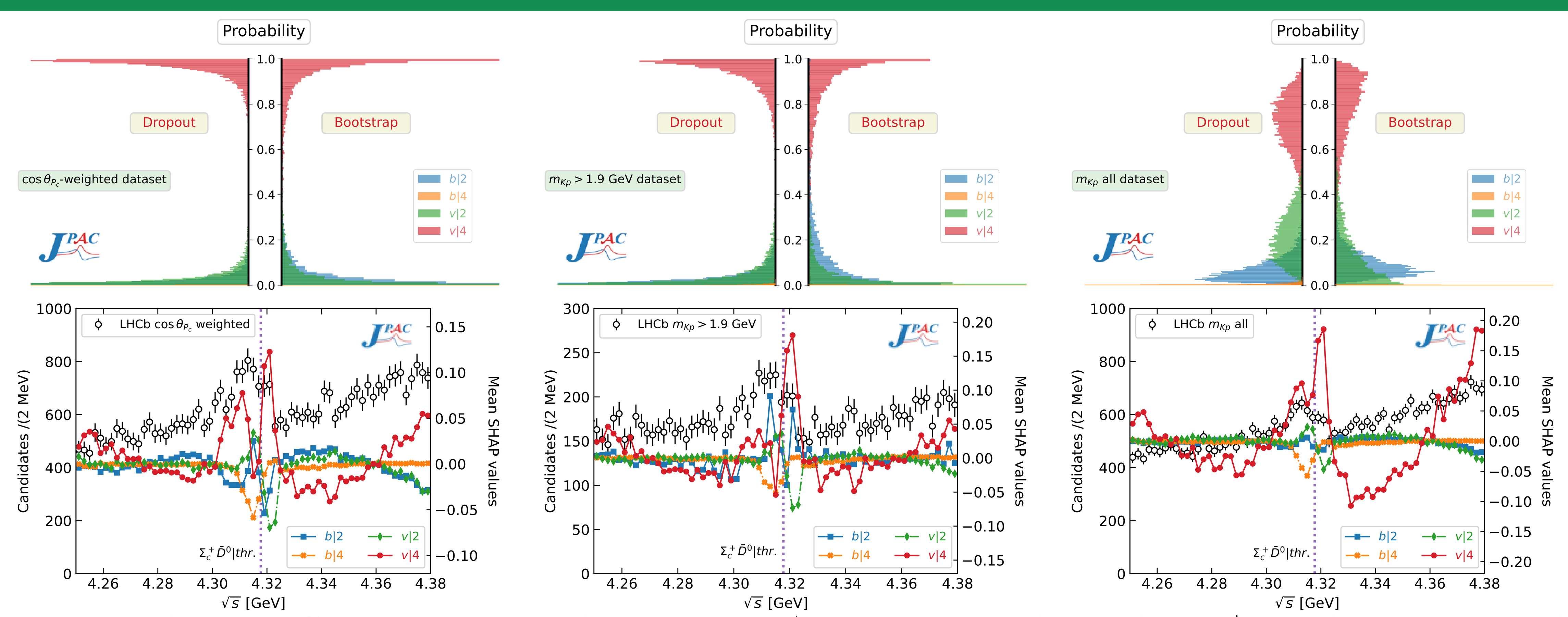


Prediction

Truth	b|2	b|4	v|2	v|4
b|2	95.6	4.3	3.7	2.2
b|4	1.9	92.2	0.0	2.8
v|2	2.0	0.1	90.4	4.3
v|4	0.5	3.3	5.8	90.7

- Prediction accuracy is better than 90% for all considered classes.

6. Predictions and Conclusions



- For three LHCb experimental data sets the ANN consistently predicts v|4 as the most probable dynamical scenario [2].
- SHAP values of the v|4 class take largest values close to the $\Sigma_c^+\bar{D}^0$ threshold, which provides an *ex post* justification of the assumed scattering length approximation.

7. References

[1] C. Fernández-Ramírez et al. "Interpretation of the LHCb $P_c(4312)$ Signal". In: *Phys.Rev.Lett.* 123.9 (2019), p. 092001.

[2] L. Ng et al. "Deep Learning Exotic Hadrons". In: *Phys.Rev.* D105 (2022), p. L091501.