Joint Physics Analysis Center Review 2022

AI/ML@JPAC

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#SOMOS2030

GOBIERNO DE ESPAÑA

MINISTERIO DE EDUCACIÓN Y FORMACIÓN PROFESIONAL

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Standard approach to data analysis of a resonance lineshape

- Take an amplitude, it has parameters to be determined by data
- Fit data using χ^2
- Extract parameters and get pole positions and compute uncertainties
- Assess the probability that those data were generated by your amplitude
- If χ^2 is reasonable, one can claim that the physical interpretation of the data is possible
- One can do this with different amplitudes that represent different underlying dynamics
- Compare amplitudes? Compare dynamics?

AI/ML

Machine Learning provides methods to learn from data to perform tasks

Widely used nowadays thanks to:

- *Improvement in algorithms and hardware*

Examples:

- *Neural networks, Random forest, Genetic algorithms, …*

Widely used in physics

- *Fitters, universal interpolators, classifiers*

Explainability

- *NNs are usually black boxes, so statistical methods have been developed to study them*

AI/ML/NNs in hadron physics

Experiments

- *Particle ID, …*

A(I)DAPT

- *Exploring NNs to extract amplitudes from data. LRDR funded*

Universal interpolators

- *NNPDF*

Regression

- *Lattice QCD*

Classifiers

- *Hadron spectroscopy (this talk)*

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., 2003.10770, 2104.141782, 2105.04898*

If possible…

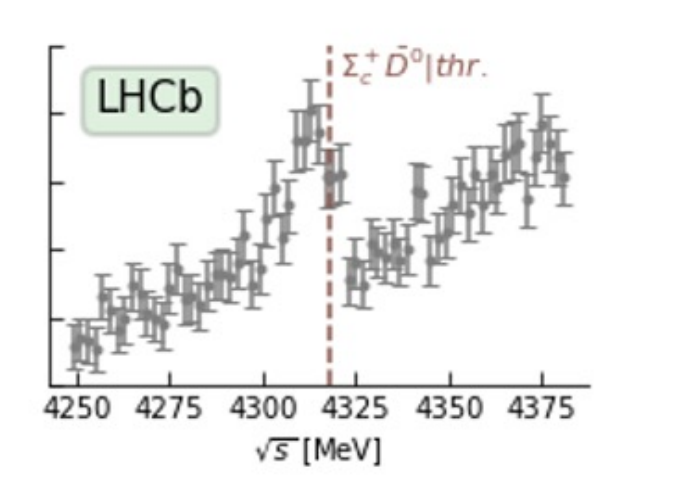
- *What other information can we gain by using machine learning techniques?*

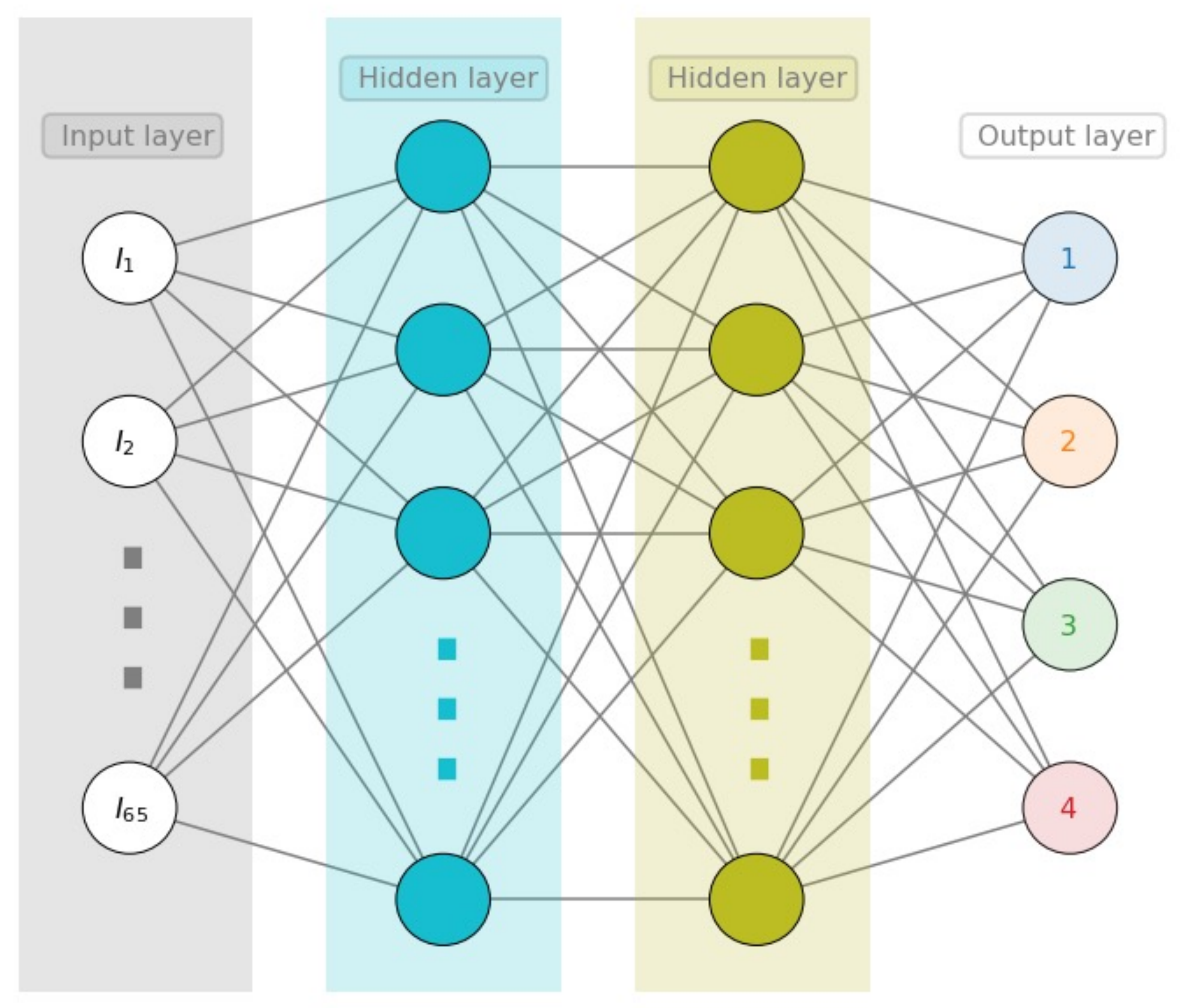
Benchmark case

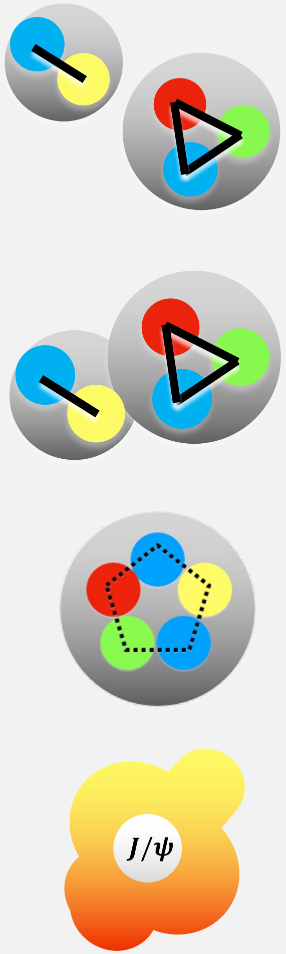
- *The $P_c(4312)$ lineshape: Ng et al. (JPAC)* 2110.13742

Still far away from answering this question but we are advancing

Holy Grail: AI as a tool for physics discovery

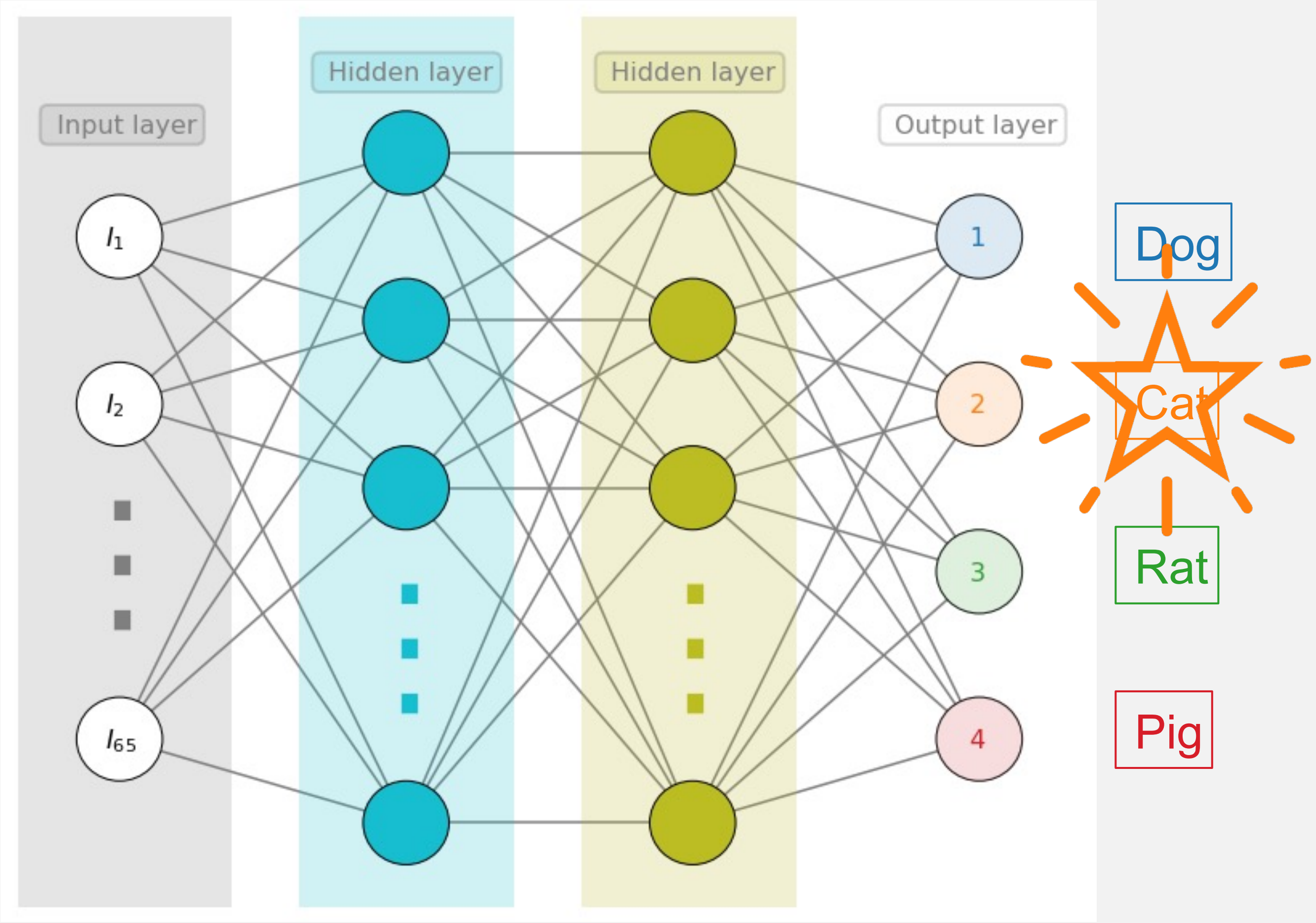






Neural networks as classifiers

Training



Neural networks as classifiers

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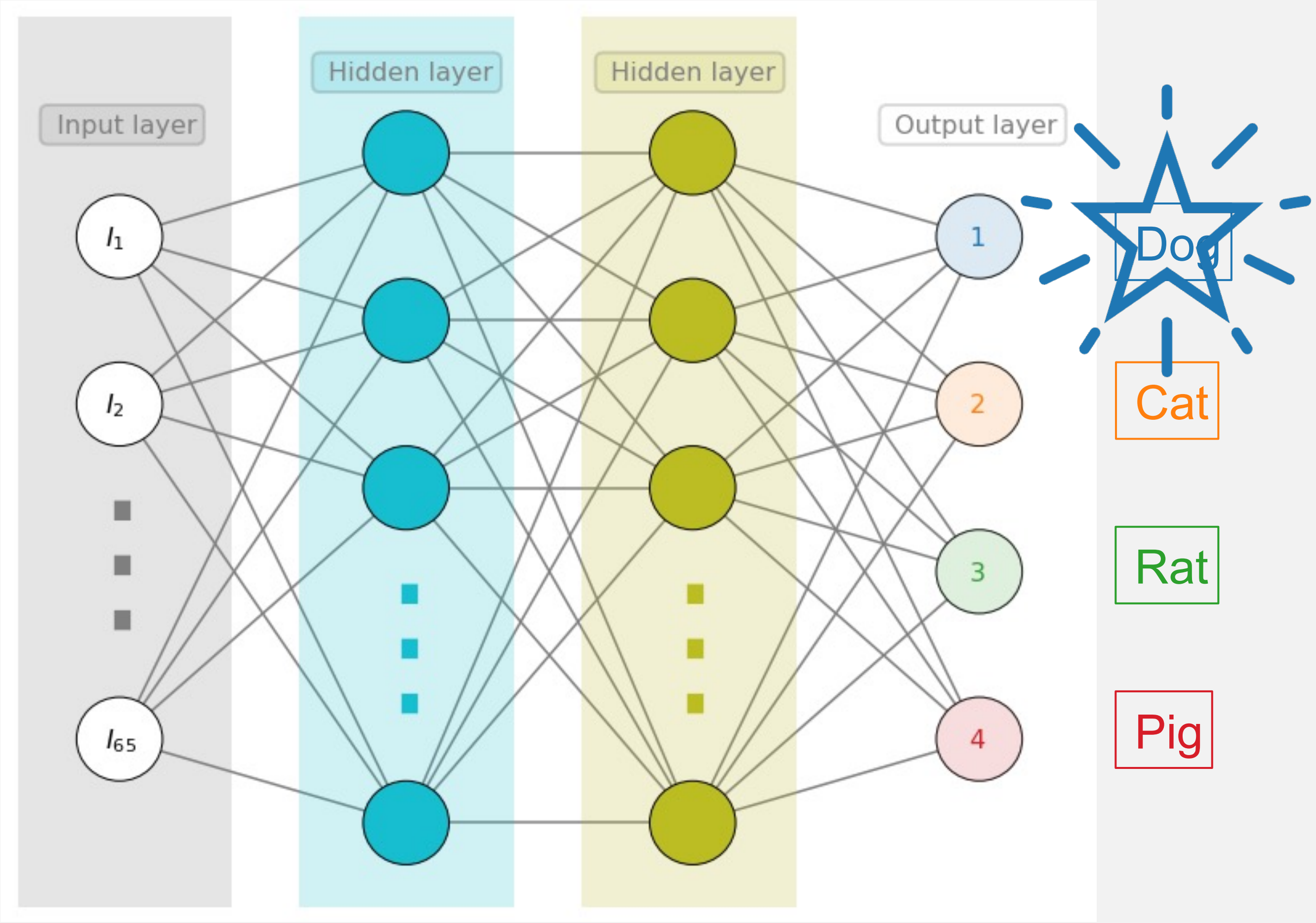

Neural networks as classifiers

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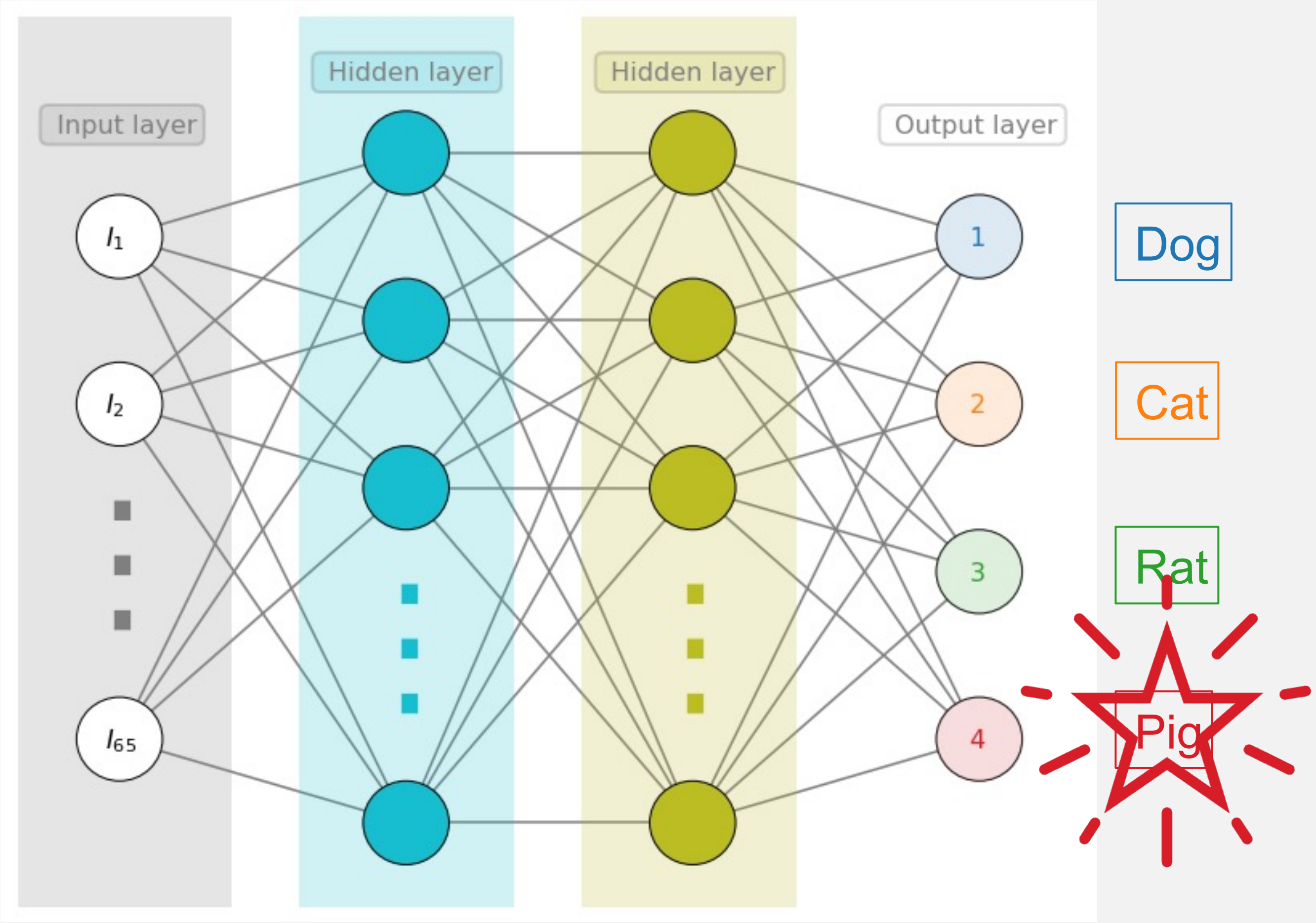

Neural networks as classifiers

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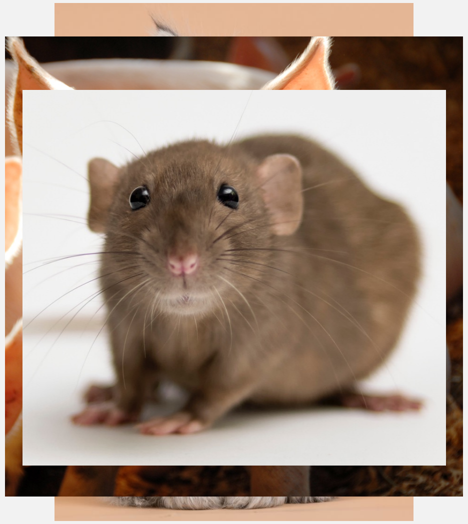

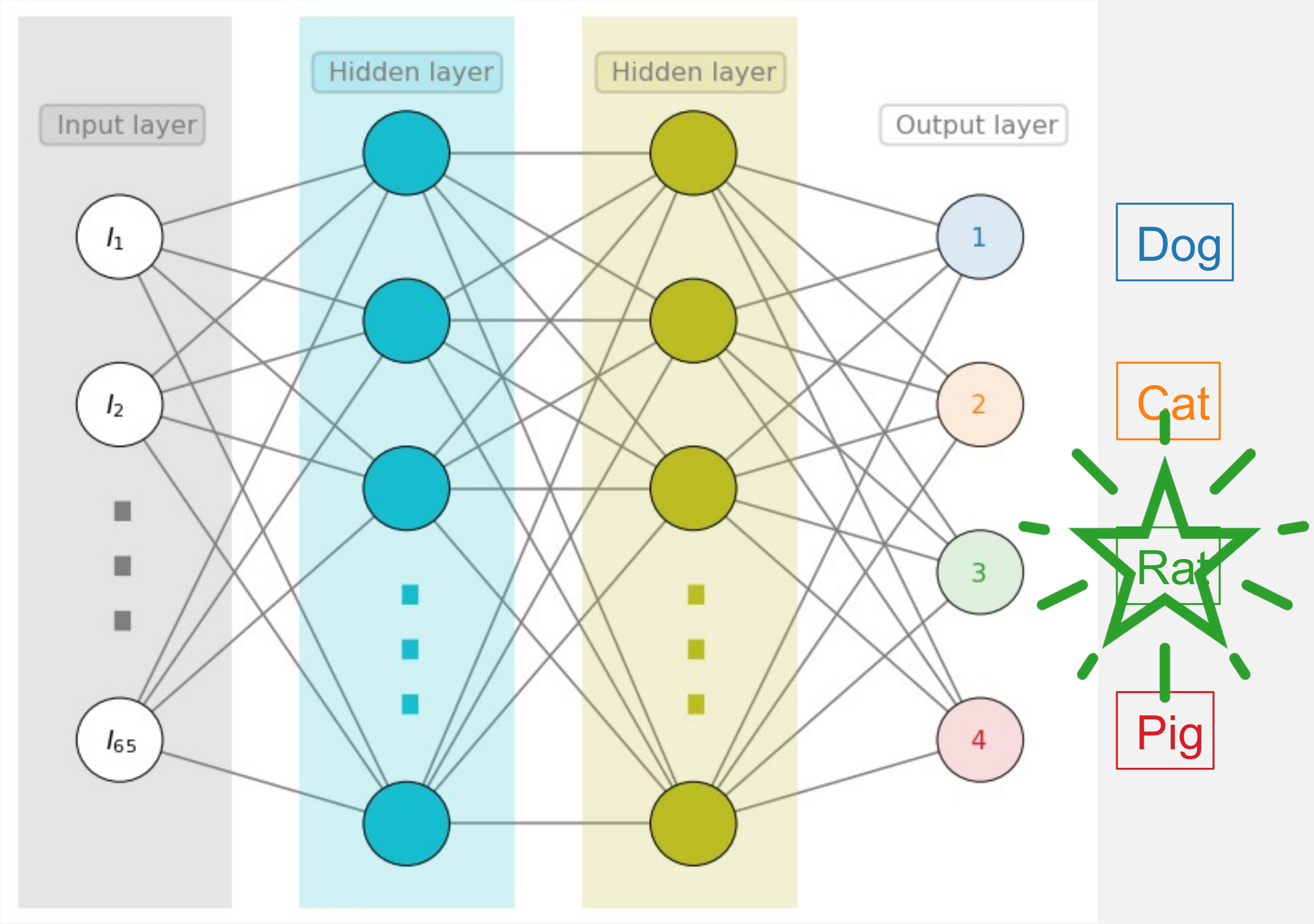

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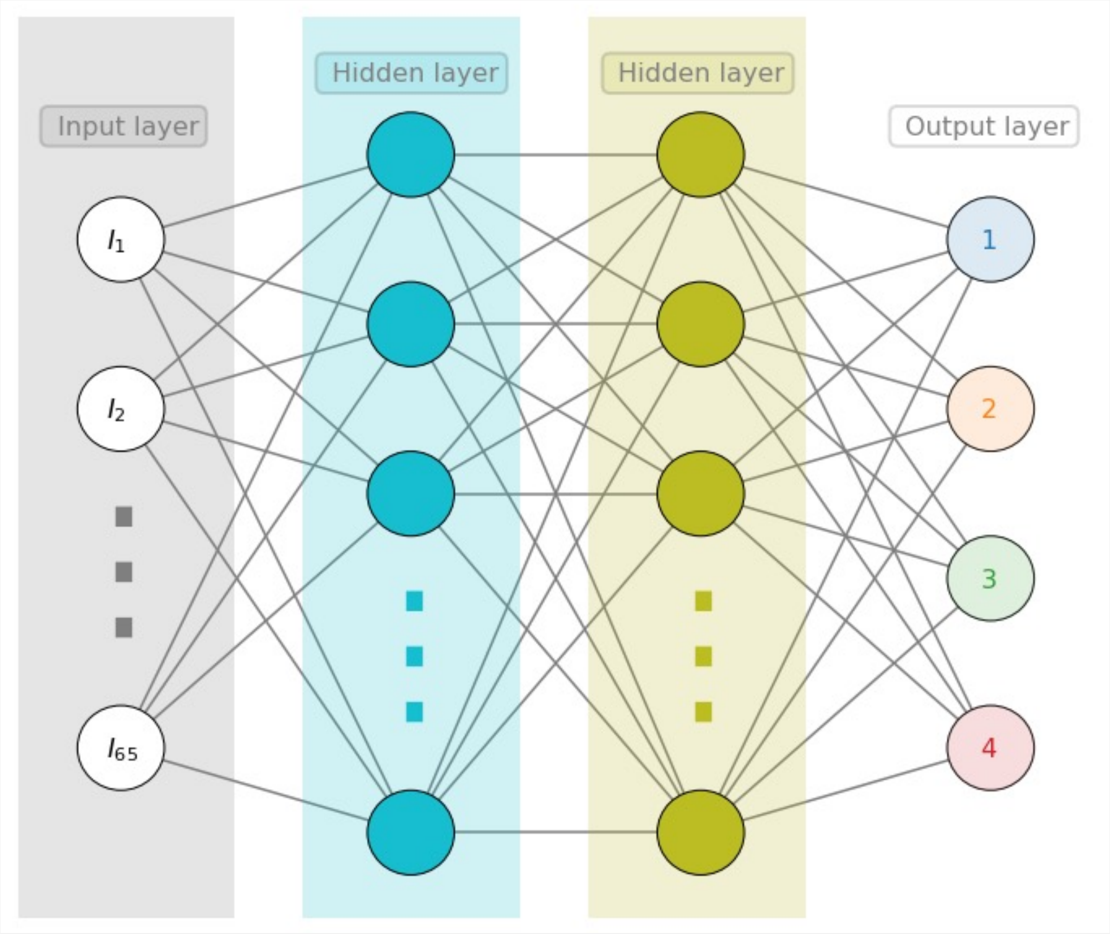
Neural networks as classifiers

New picture



Dog	3%
Cat	96.8%
Rat	0.1%
Pig	0.1%

Disclaimer: Made up percentages

Building a benchmark

Training the neural network

- *We choose a model that we fully understand to teach the NN about lineshapes*

Comparison

- *Simple enough to perform a direct comparison between standard and NN approaches*

Experimental data

- *We use the model on data that we know well*

Error analysis

- *Implement uncertainites both in the training and the data analysis*

Building the training set

10^5 training curves

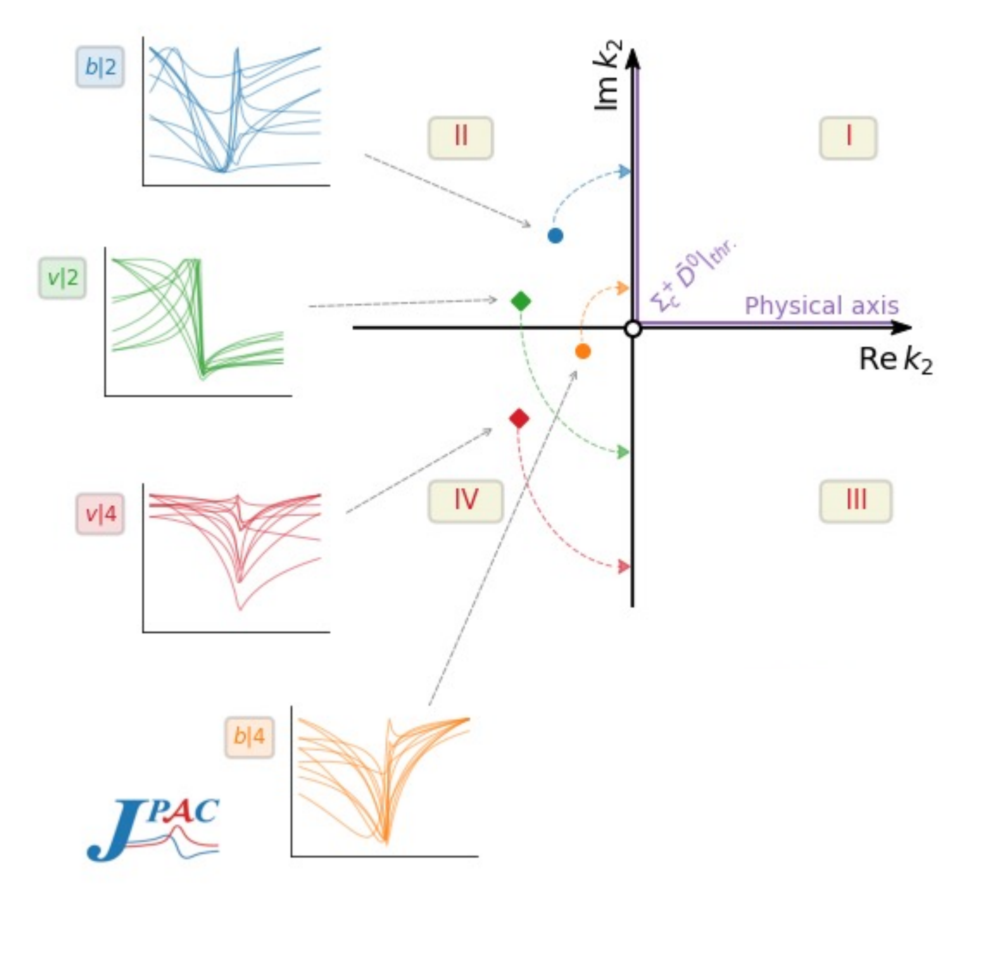
- *Generated by randomly setting parameter values in a wide range*
- *Curves are computed at the experimental energies*

Convolution

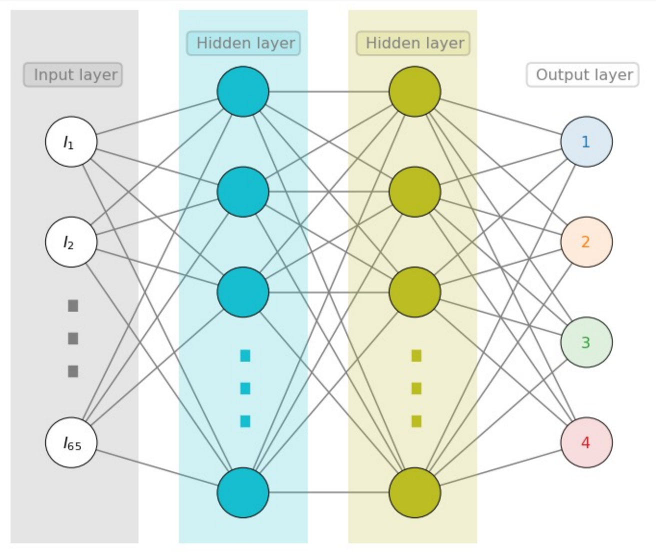
- *Model is convoluted with the experimental resolution*

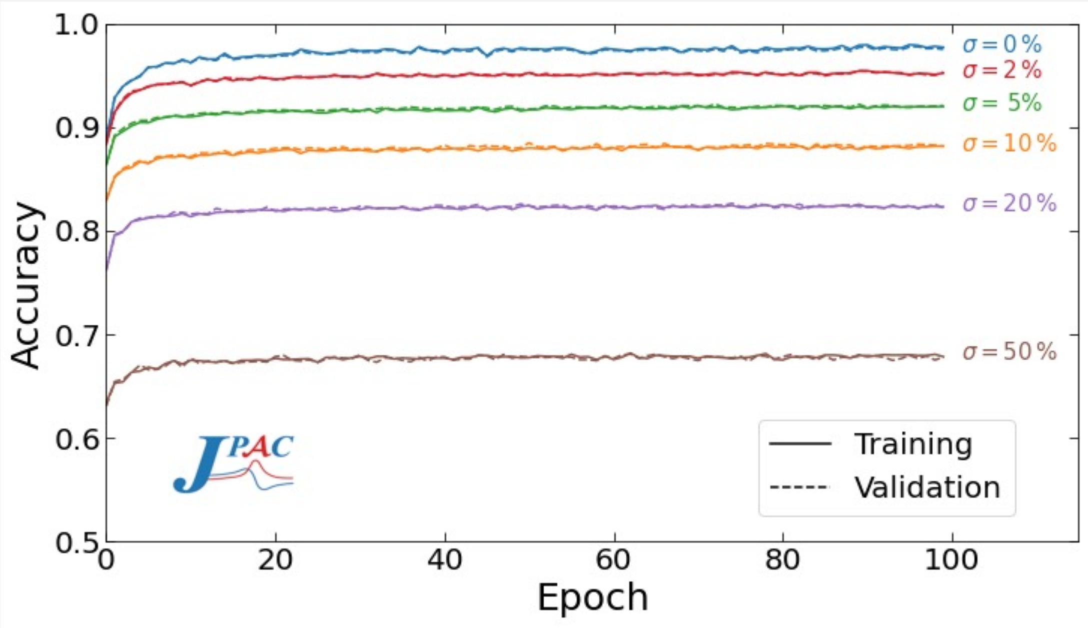
Gaussian noise

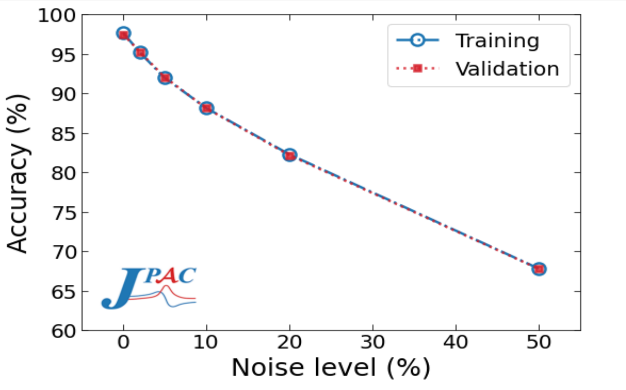
- *Included to mimic uncertainties*
- *Compare "blurry" to "blurry"*

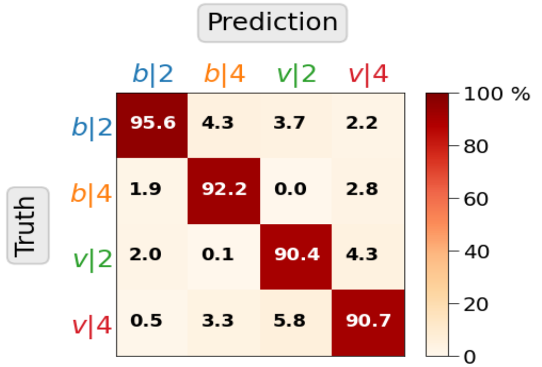


Training / validation









Training determines the parameters (weights) of the NN

Experimental uncertainties: bootstrap

Associate a distribution to each experimental datapoint

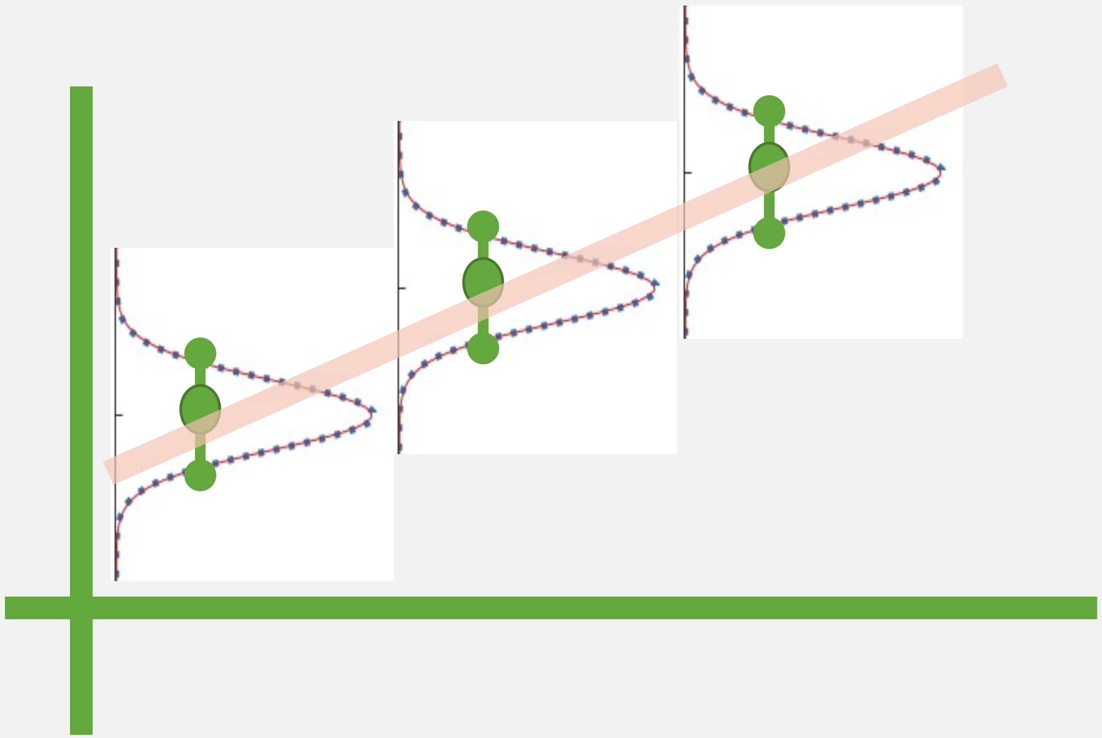
- *Typically a Gaussian with mean and sigma from experiment*

Monte Carlo

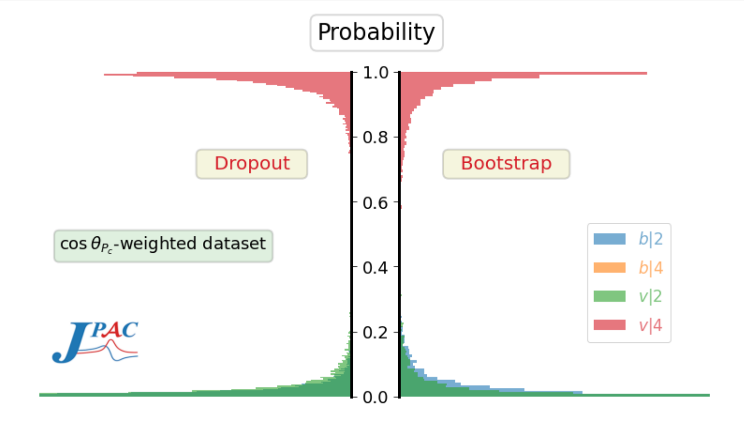
- *Generate pseudodata according to the chosen distribution*

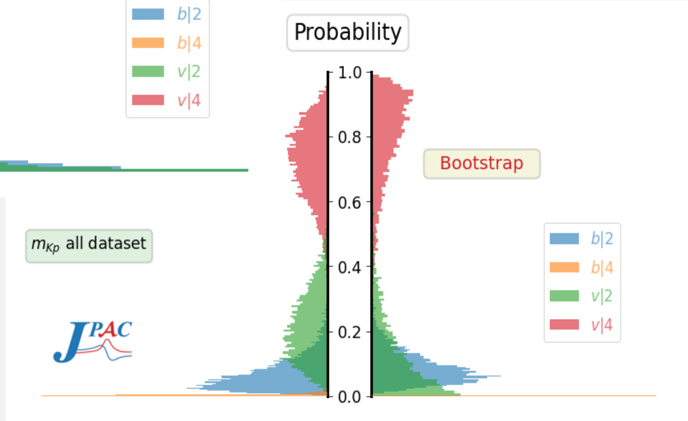
Run statistics on the pseudodatasets

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



Applying the NN to LHCb data





	$b\|2$	$b\|4$	$v\|2$	$v\|4$
$\cos\theta_{P_c}$-weighted	0.6%	$<$ 0.01%	1.1%	98.3%
$m_{Kp} > 1.9\,\mathrm{GeV}$	1.4%	$<$ 0.1%	1.6%	97.0%
m_{Kp} all	5.4%	$<$ 0.1%	21.0%	73.6%

We pass the data through the NN

- *We pass the three LHCb datasets through the same NN to obtain three answers*

Uncertainties

- *Bootstrap and dropout*

Obtain proability distributions

- *Sanity check: We recover the same result as with the standard approach: v|4*

What we get from the NN

The NN is comprehensive exploring the parameter space

Standard χ^2fit are often unstable and NN can help exploring the parameter space

Rather than testing a single model hypothesis, the NN tests various models all at once

But, there's more…

Explainability

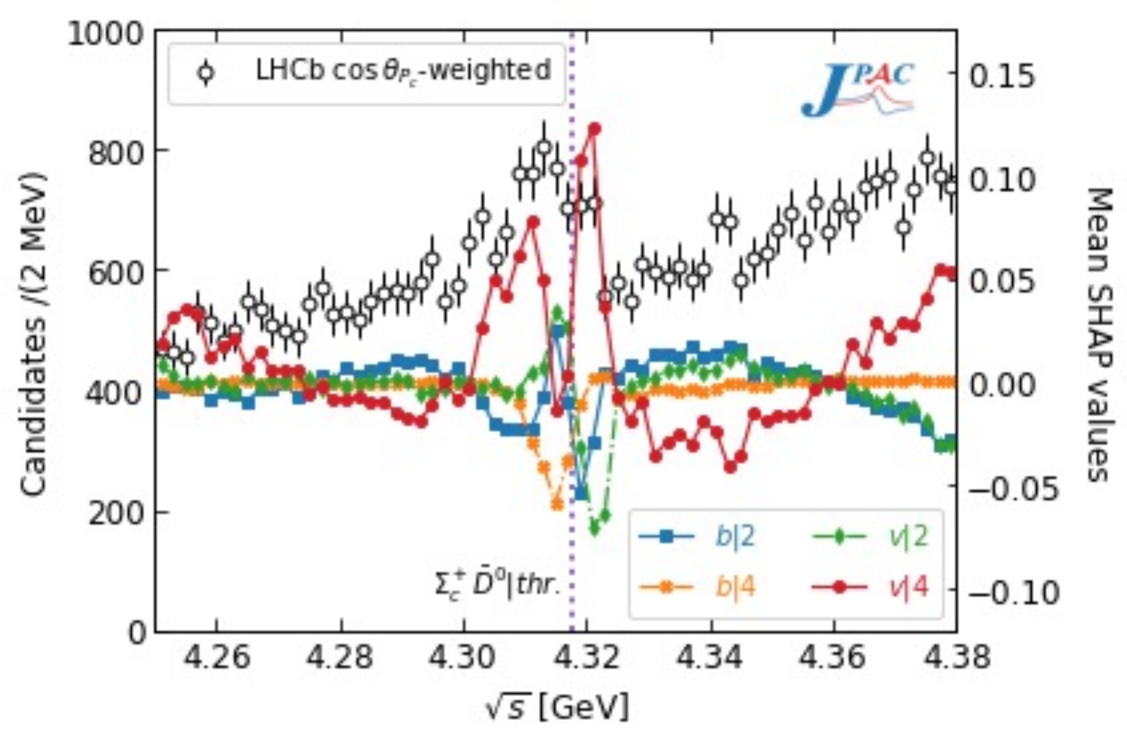
SHAP values

- *SHapley Additive exPlanations*

Inherited from game theory

Application

- *Allows to determine how a given feature in the input layer (in our case an experimental datapoint) impacts the decision made by the NN in the output layer (the classes)*



Takeaways

We tested a relatively simple, ML based application, and we are positively surprised by the results

- *Ng et al. (JPAC), 2110.13742*

We started as skeptics and became excited about AI/ML

- *Engaging topic for prospect students*

NN is not a substitution of the canonical approach to analyzing data

We are (hopefully) just in the begining…