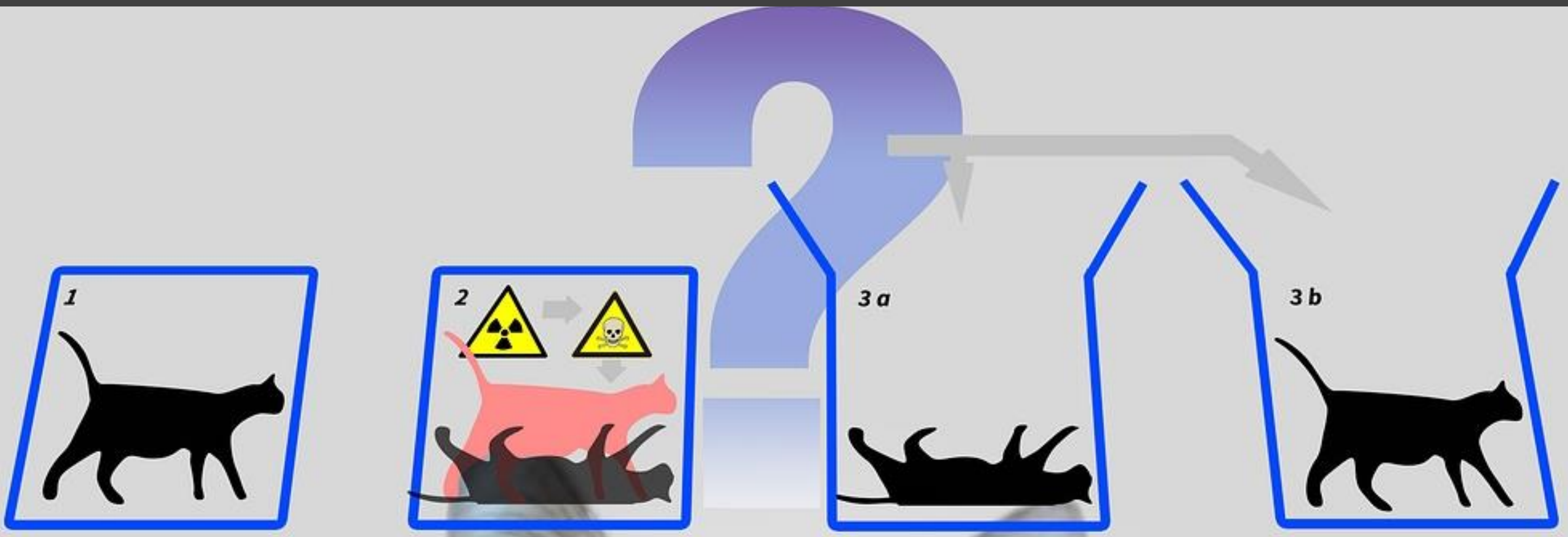


MENICA DIBENEDETTO, ASSISTANT PROFESSOR @MAASTRICHT UNIVERSITY

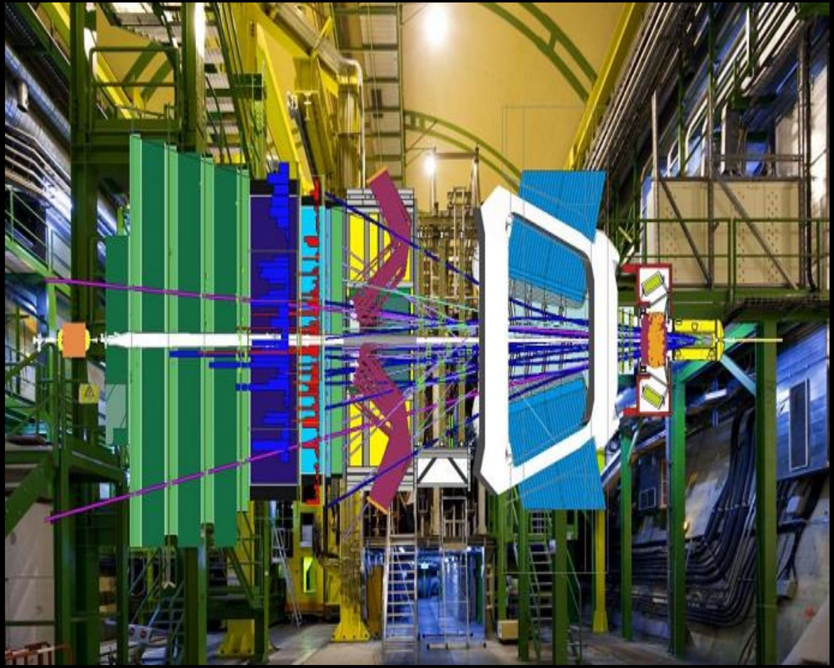
Quantum Machine Learning for Physics

Quantum approach based on Ising Model for physics data

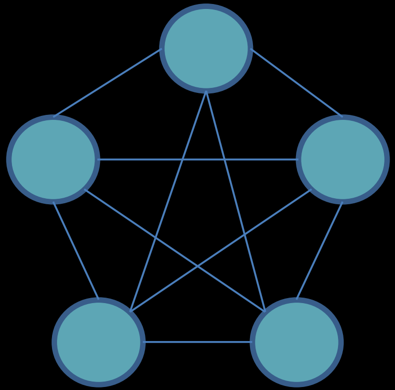
SUBMITTED

Why?

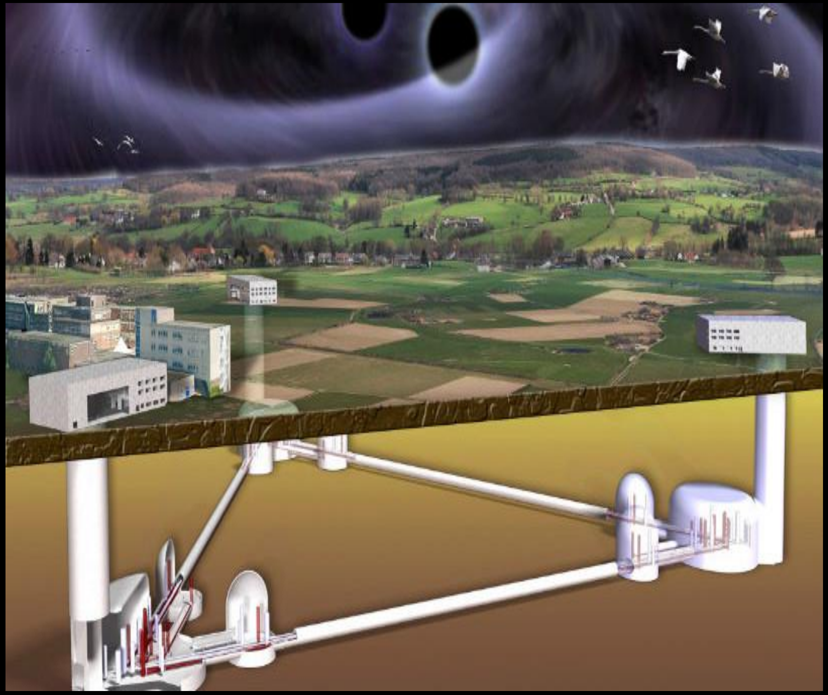
Tracking @LHCb



Quantum Hopfield Network



GW / ETpathfinder



Ising Model

Connection..

PHYSICS

Data from LHCb and GW

MACHINE LEARNING

Hopfield Network

- Quantum Hopfield Neural Network for Gravitational Waves detection and characterization
- Quantum Hopfield Neural Network for tracking problems at LHCb

QML and Ising model

- **SPIN-GLASS MODEL**

  interplay of disorder and fluctuations in physical systems from atomic to planetary scale

- **ISING MODEL**

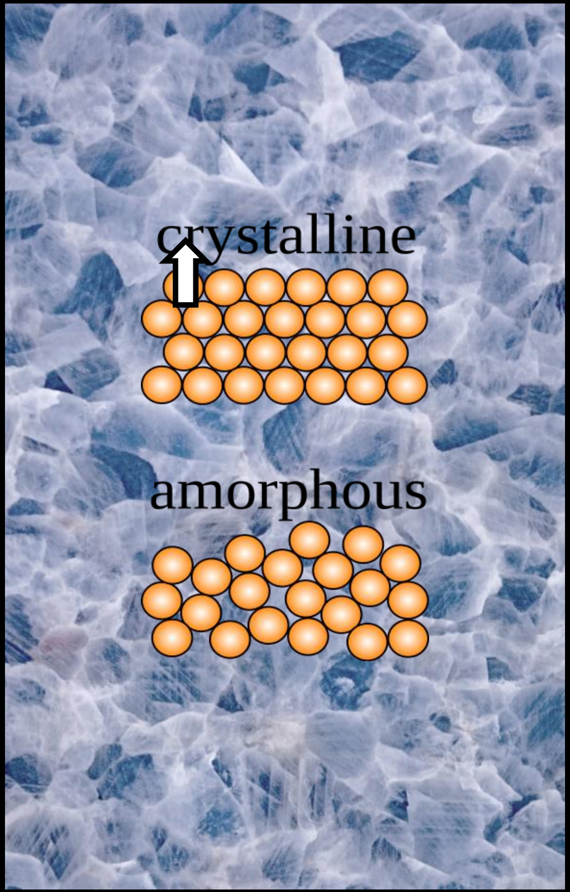
  explain ferromagnetic behaviour (application of Boltzman distribution)

- **HOPFIELD NEURAL NETWORK**

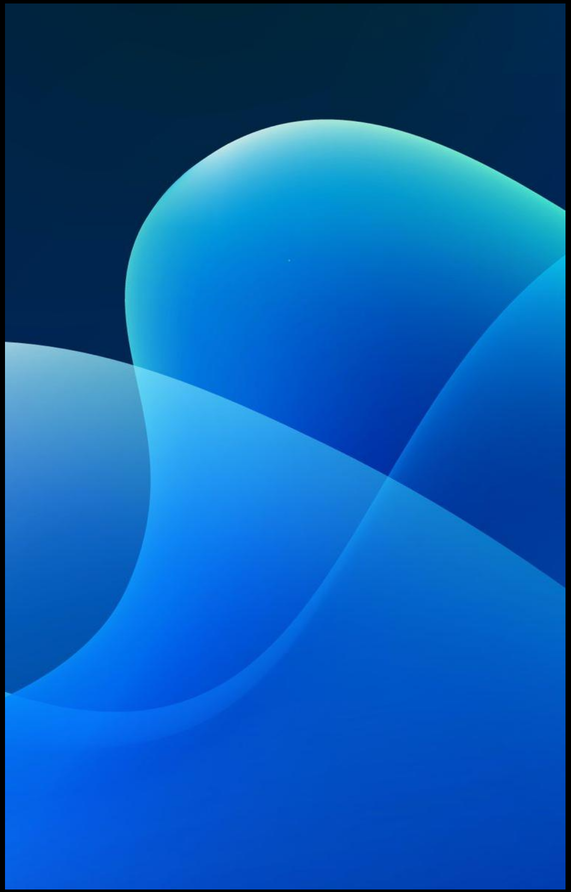
  Connection between ANN and our brain

Spin-glasses

COMPLEX SYSTEM



DISORDER



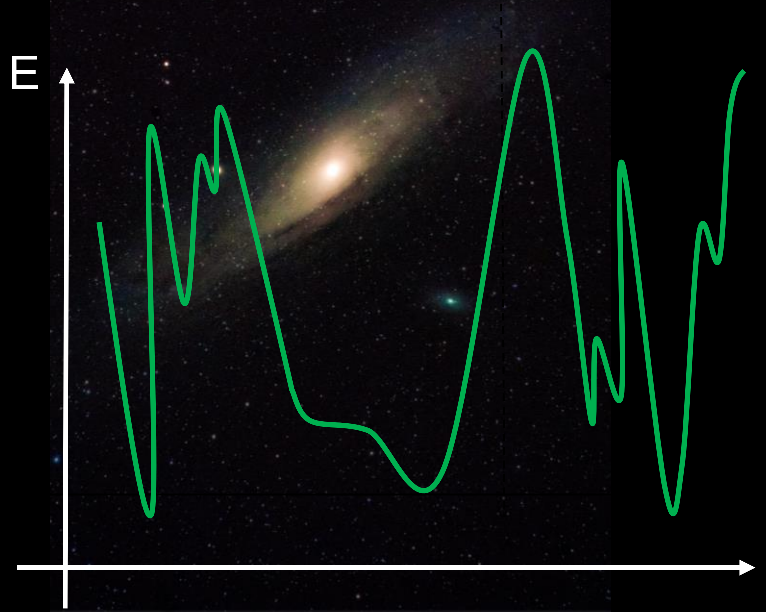
FLUCTUATIONS

FRUSTRATION

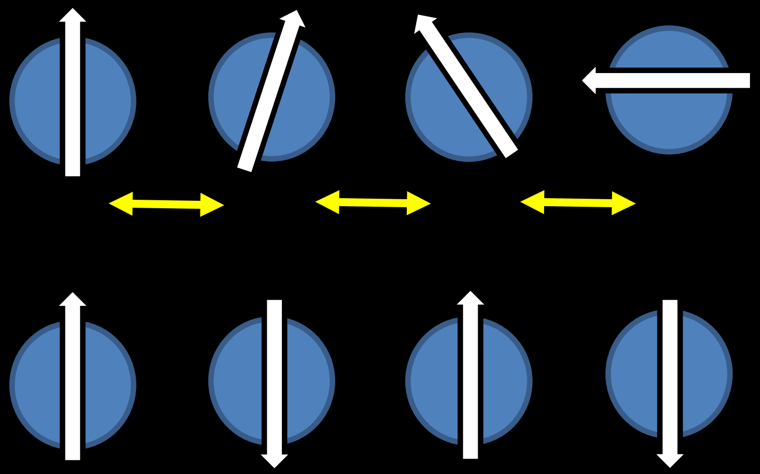
From Spin-glasses to Ising spin

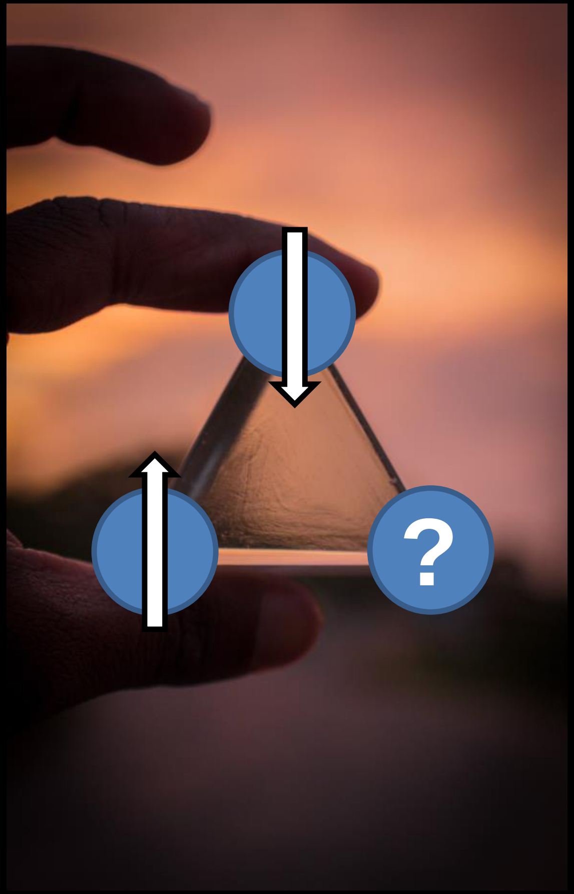
$$E(s) = -\frac{1}{2}\sum_{ij} J_{ij}\, s_i s_j - \sum_{j} h_j s_j$$

(QUBO: $\min_s$ E(s))



$$H = \sum_i J\, s_i s_{i+1} \qquad s_i = \pm 1$$





COMPLEX SYSTEM

DISORDER

FLUCTUATIONS

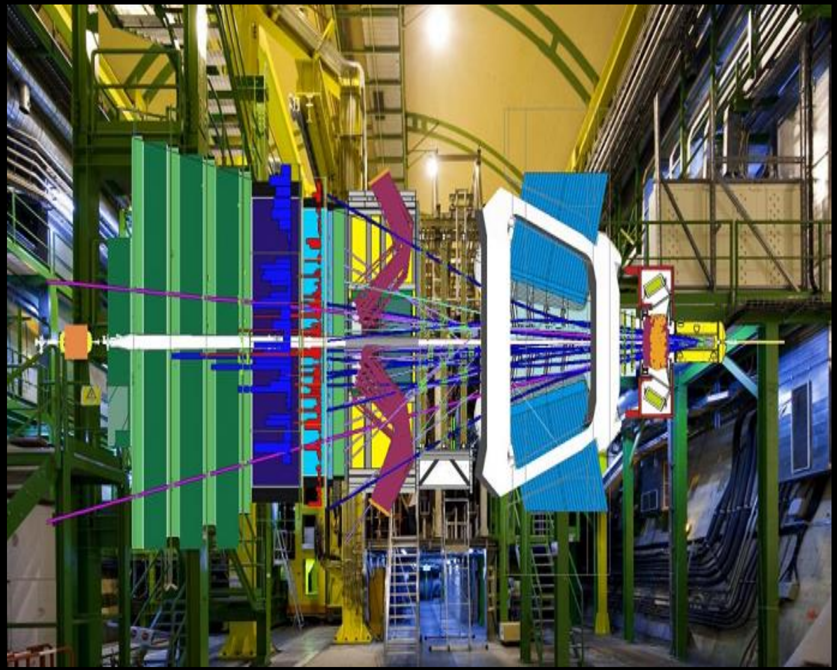
FRUSTRATION

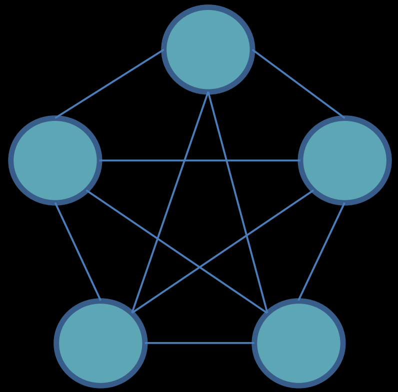
What?

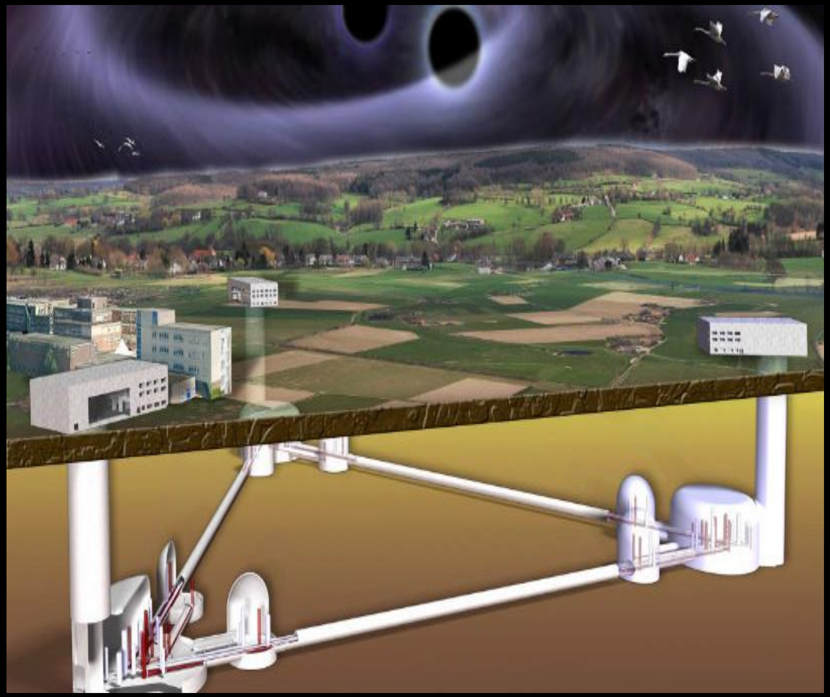
Tracking @LHCb

Quantum Hopfield Network

GW / ETpathfinder







Hopfield Network

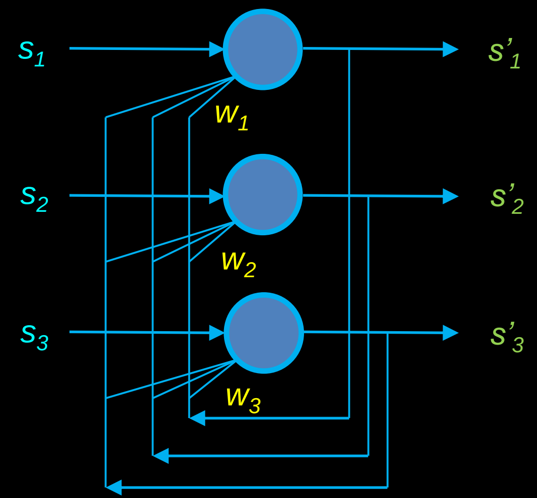
Rest in local minimum state, associate a new input with a spurious state
Number of sample ~ size of sample (impractical for large number of n)

1 SINGLE LAYER, RECURRENT, FULLY CONNECTED BINARY NEURONAL NETWORK

2 SYMMETRIC WEIGHT MATRICES, HEBBIAN LEARNING RULE

3 THE DYNAMICS OF THE NETWORK RESEMBLES THAT OF AN ISING MODEL AT LOW TEMPERATURES

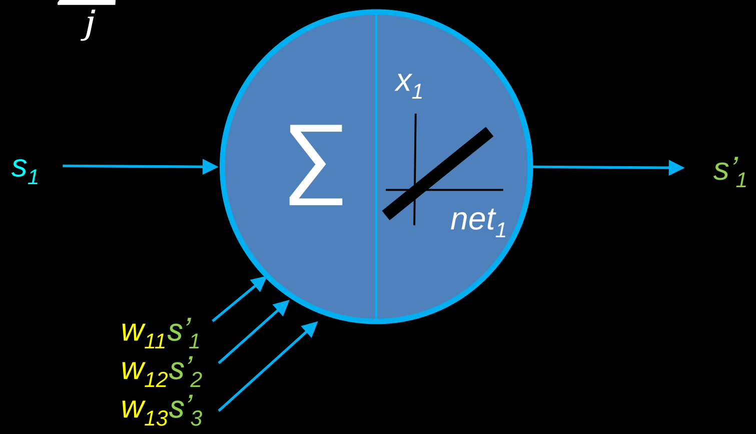
4 A RANDOMLY CHOSEN INITIAL STATE WILL CONVERGE TO ONE OF THE MEMORIZED STATES



$$E(s) = -\frac{1}{2}\sum_{ij} w_{ij}\, s_i s_j - \sum_j h_j s_j$$

$$w_{ij} = \frac{1}{N}\sum_{\mu} \sigma_i^{\mu}\sigma_j^{\mu}$$

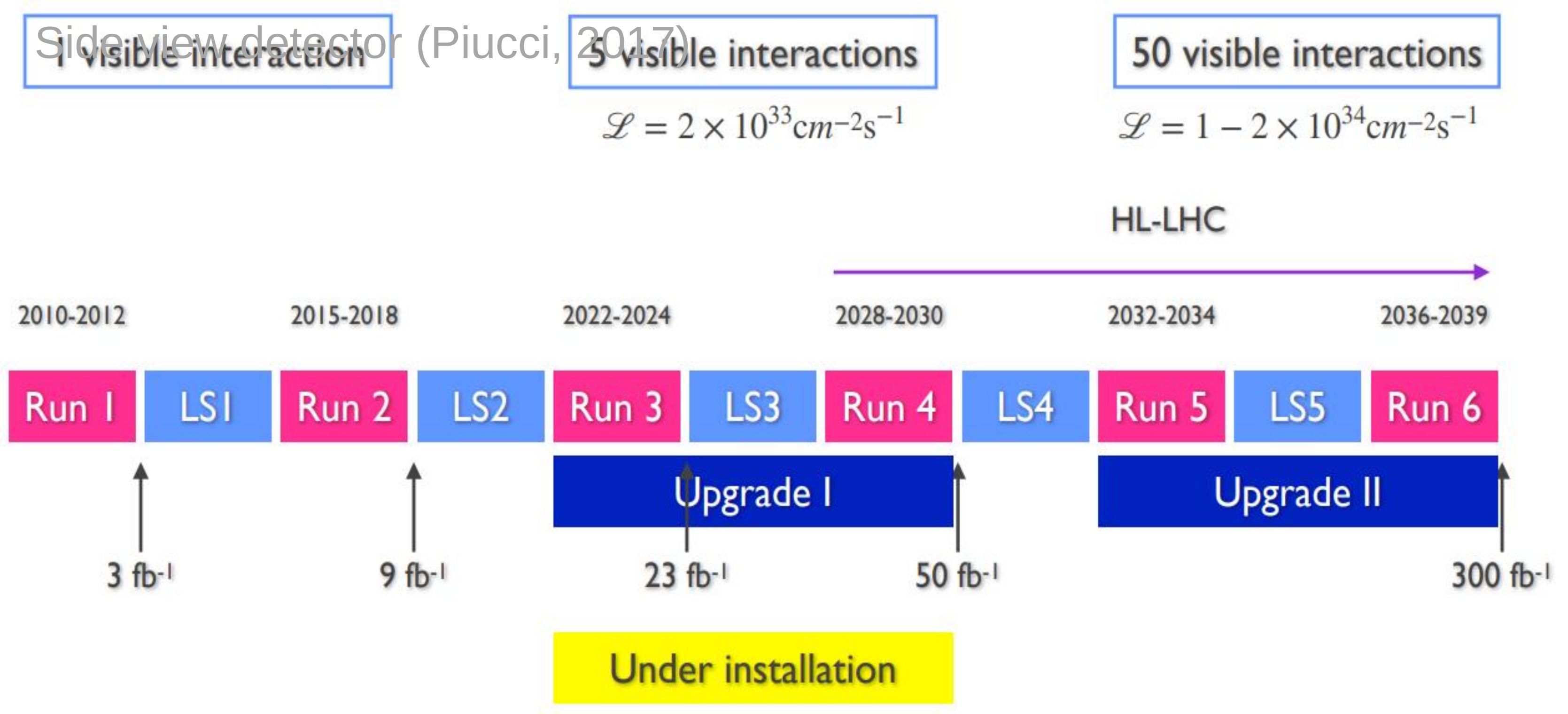
$$s_i' = sgn(w_{ij}s_j - h_j)$$

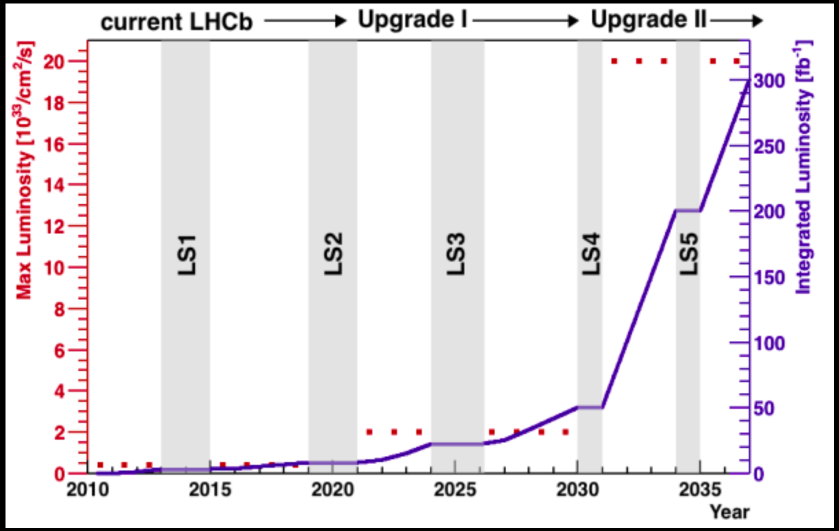


Applications LHCb tracking problems

Tracking problem: given a set of hits, cluster them into collection of hits that come from the same particle

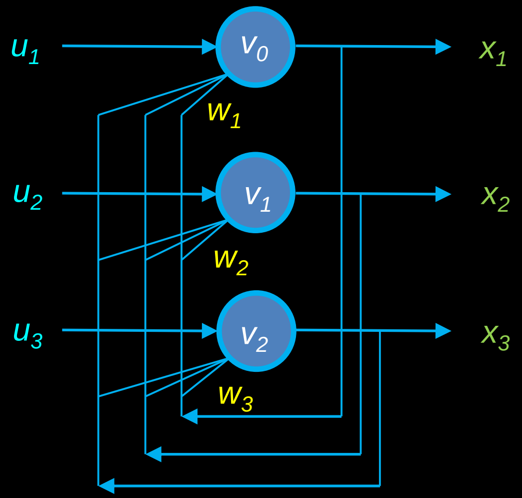
Side view detector (Piucci, 2017)

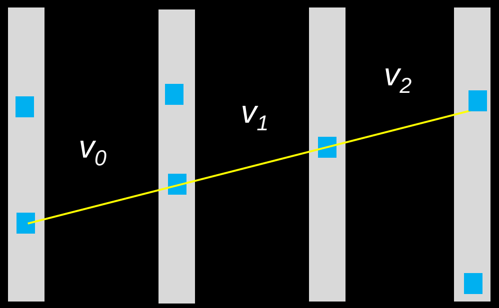


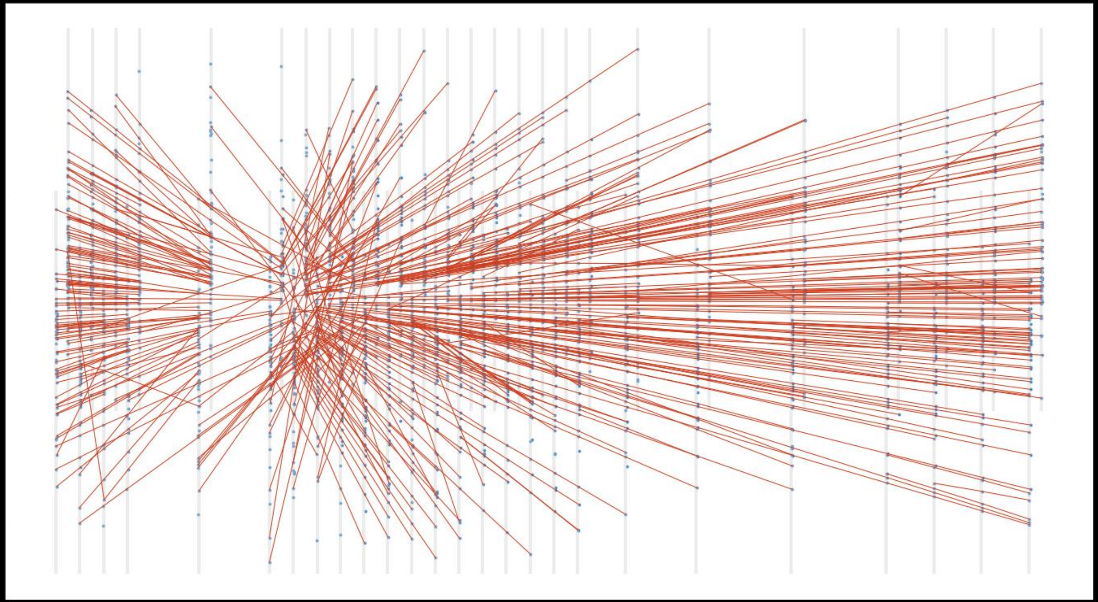


The LHCb Upgrade: Data bandwidth is **limited** → we will need to reconstruct events 40 Million times per second!

Applications LHCb tracking problems



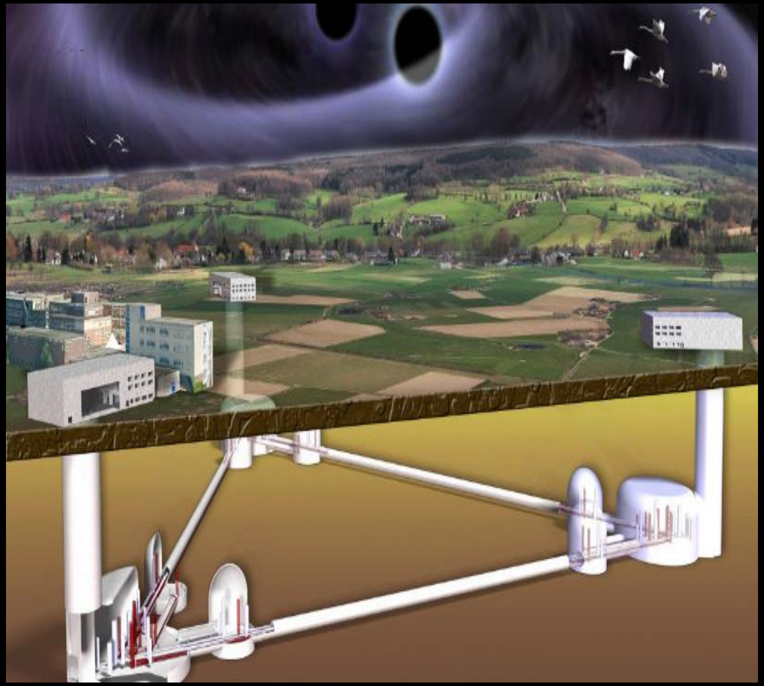




- NN can deal with situations of information erasure
  (not all tracks will leave a hit in each one of the sub-detectors)
- Previous work has been done with Hopfield networks in the LHCb Muon system (A Recurrent Neural Network for Track Reconstruction in the LHCb Muon System Giovanni Passaleva, 2008)

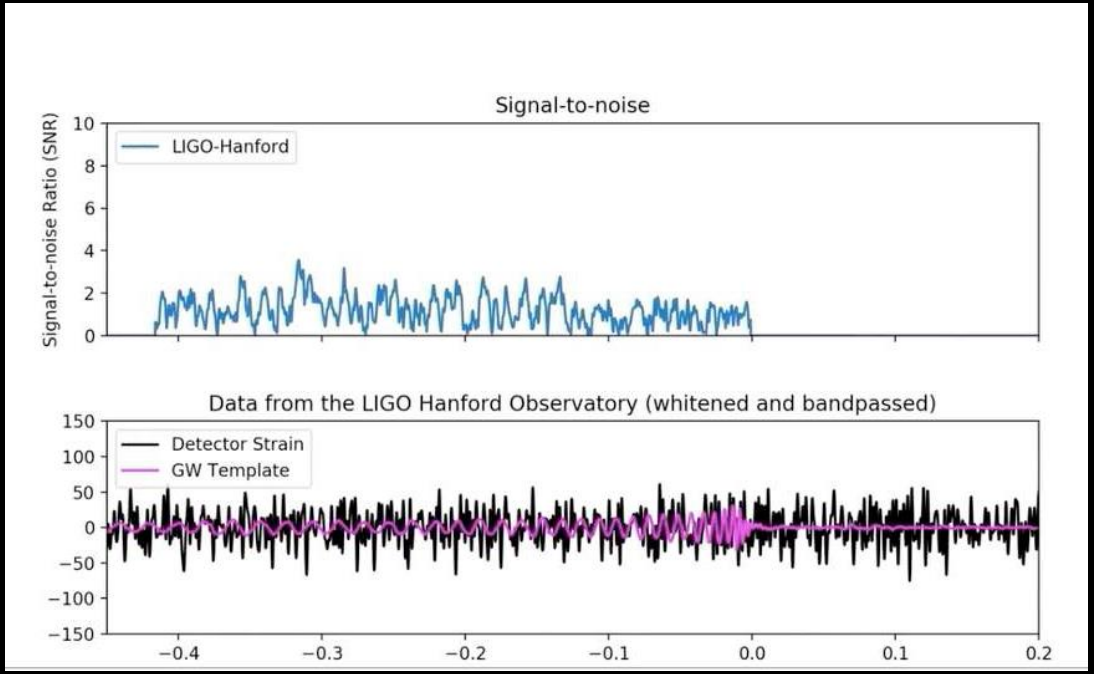
Applications GW/ETpathfinder

Next generation of detectors
(Einstein Telescope, Cosmic explorer)



- Increase in sample size
- Increase in details: broader frequency range
- Increase in volume: overlap continuously

The matched-filtering method



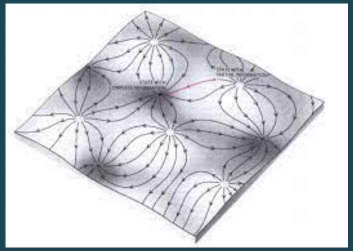
- Need for pre-calculated templates
- Each template depends on multiple parameters (parameter space can be up to fifteen-dimensional)
- The template has to be matched over a much longer period of time and many gravitational signals will be ongoing at any given time

Applications GW/ETpathfinder

Pattern recognition

HN as pattern recognition algorithm for detection and characterization of GW signal

Quantum:
Liu, G., Ma, W.-P., Cao, H. & Lyu, L.-D. A quantum Hopfield neural network model and image recognition. Laser Phys. Lett. 17, 045201 (2020).



Signal denoising

- to recover the gravitational wave signals
- integrated as a step of data cleaning for quantum or classical algorithms
- increase the efficiency and precision of an algorithm

Quantum:
Clift, F. & Martinez, T. R. Improved Hopfield networks by training with noisy data. in IJCNN’01. International Joint Conference on Neural Networks. Proceedings (Cat. No.01CH37222) vol. 2 1138–1143 (IEEE, 2001).

Bhattacharyya, S., Pal, P. & Bhowmick, S. Binary image denoising using a quantum multilayer self organizing neural network. Appl. Soft Comput. 24, 717–729 (2014).

Parameters optimization for quantum partial differential equation solving algorithm

Einstein Field Equations

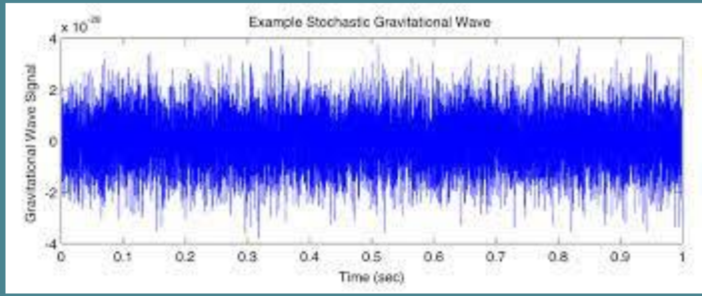
$$R_{\mu\nu} - \frac{1}{2} g_{\mu\nu} R = -\frac{8\pi G}{c^4} T_{\mu\nu}$$

optimization of parameters step

Classical:
Kyriienko, O., Paine, A. E. & Elfving, V. E. Solving nonlinear differential equations with differentiable quantum circuits. Phys. Rev. A 103, 052416 (2021).

Temporal structure discovery

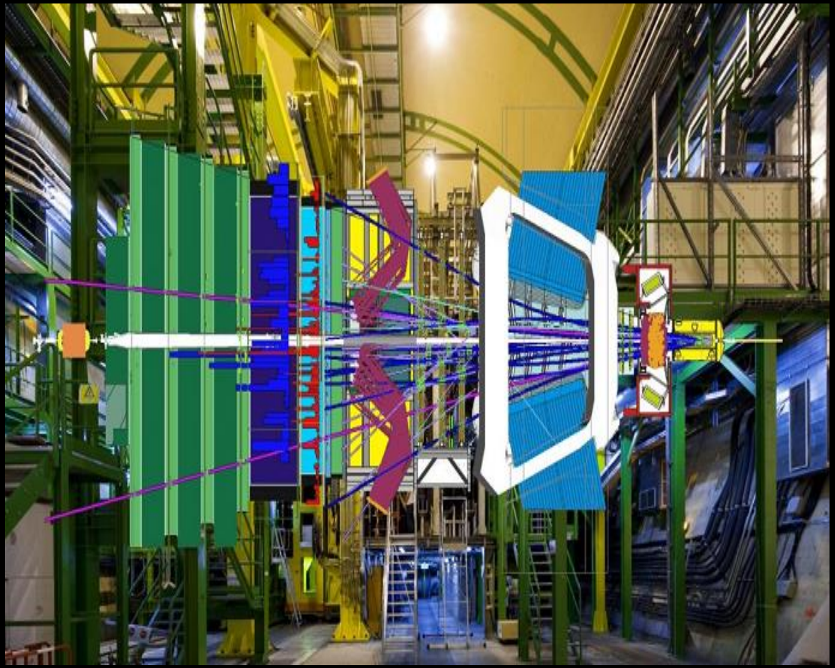
Long weak signal



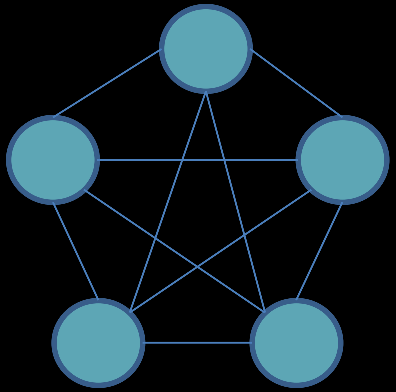
Classical:
Hillar, C. & Effenberger, F. Robust Discovery of Temporal Structure in Multi-neuron Recordings Using Hopfield Networks. Procedia Comput. Sci. 53, 365–374 (2015).

How?

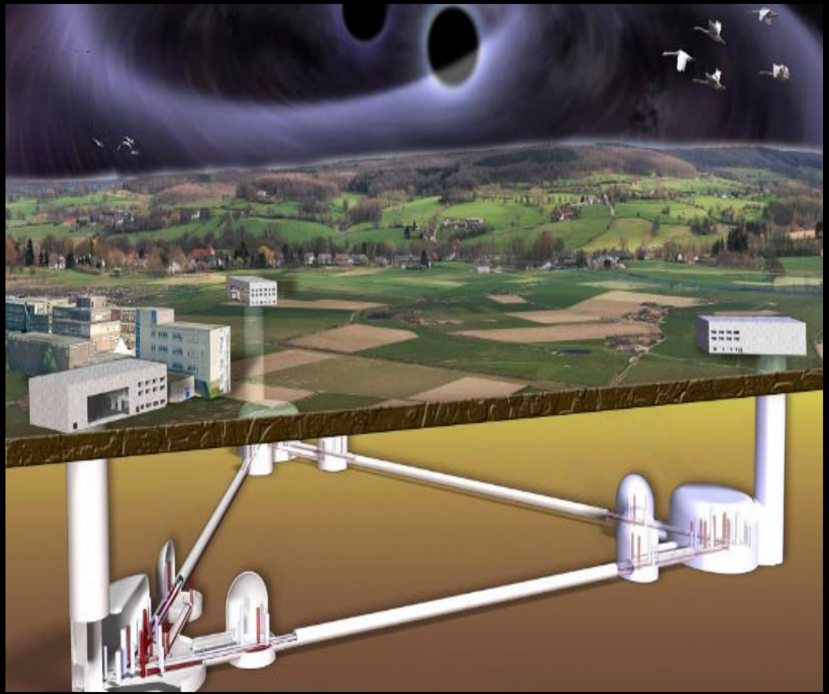
Tracking @LHCb



Quantum Hopfield Network



GW / ETpathfinder



Quantum Hopfield Neural Network

- Transverse-field Ising model

$$E(s) = -\frac{1}{2}\sum_{ij} w_{ij}\, s_i s_j - \sum_j h_j s_j \longrightarrow H = -\frac{1}{2}\sum_{ij} w_{ij}\, \sigma_i^z \sigma_j^z - \sum_j h_j \sigma_j^z - \sum_j c_j \sigma_j^x$$

$$w_{ij} = \frac{1}{N}\sum_{\mu} \sigma_i^{\mu} \sigma_j^{\mu} \qquad \sigma^z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \qquad \sigma^x = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

- Quantum extension of the differential equation of the system (Rotondo et al, 2018), able to store 2^n neurons in an n-qubit system.

How? to (re)formulate discrete optimisation problems such that they can be solved using HNs ?

Step 1: development of new and/or adapted QHN variants

Step 2: translation of the proposed problems into a specific QHN model

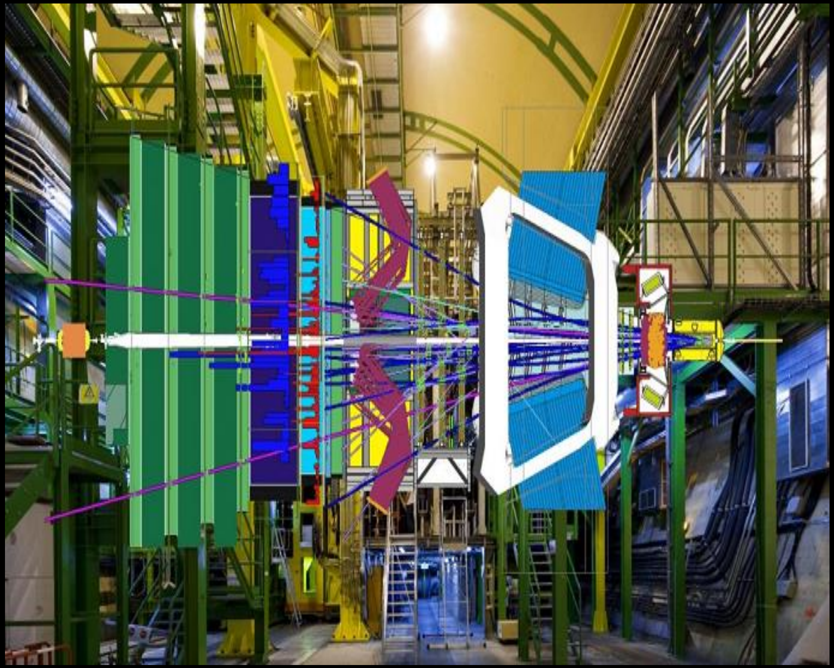
Step 3: development of a protocol for the design, validation and debugging of the developed model

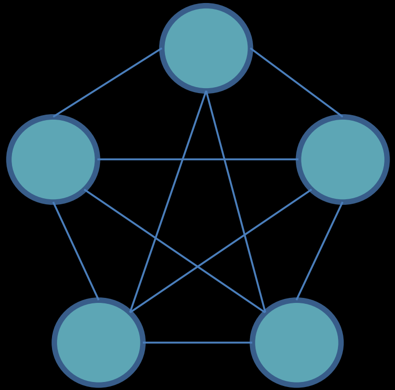
Step 4: embedding of the protocol in a quantum toolbox and assessment of its implementation in quantum hardware and its suitability for large-scale quantum simulators

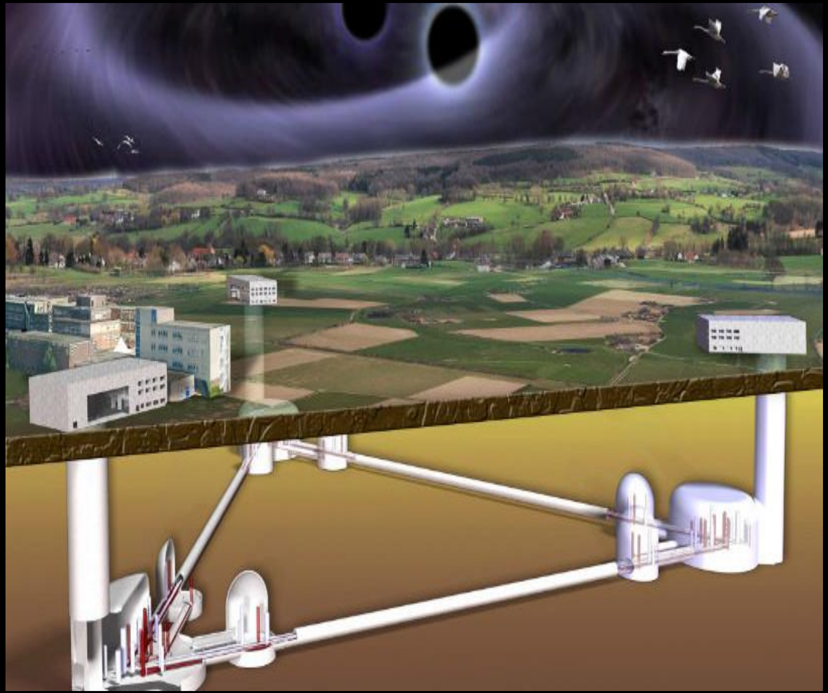
Tracking @LHCb

Quantum Hopfield Network

GW / ETpathfinder

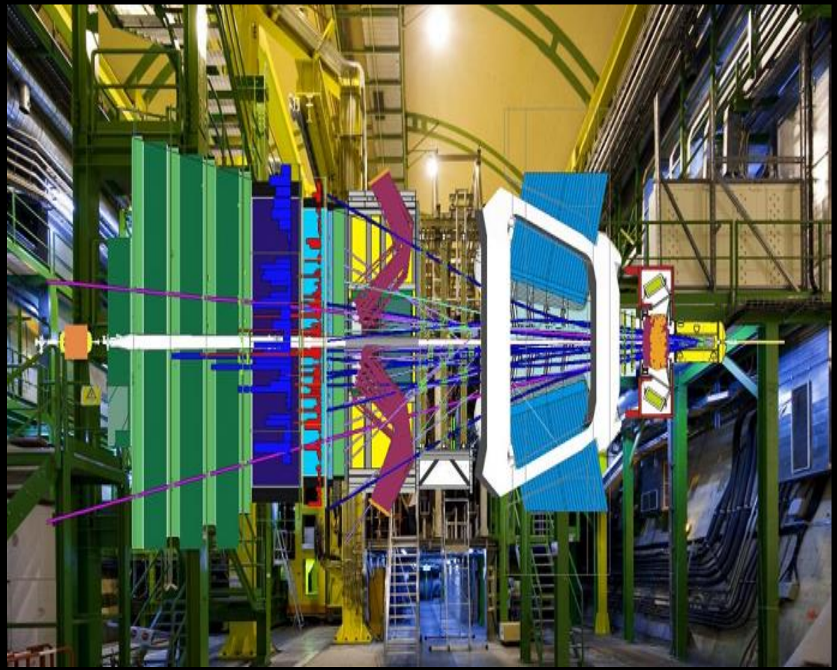




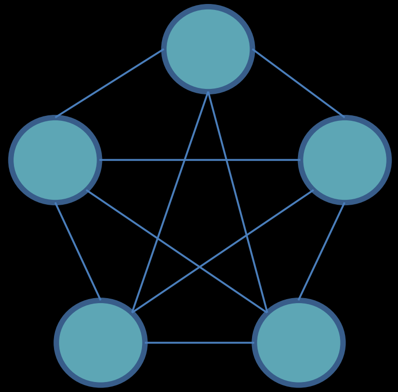


Free attempts

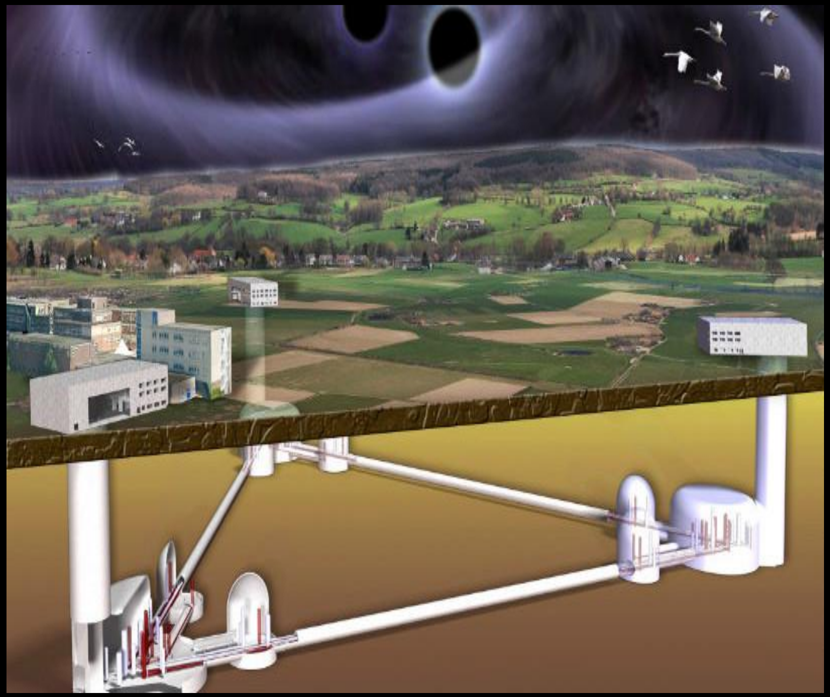
Tracking @LHCb



Quantum Hopfield Network



GW / ETpathfinder

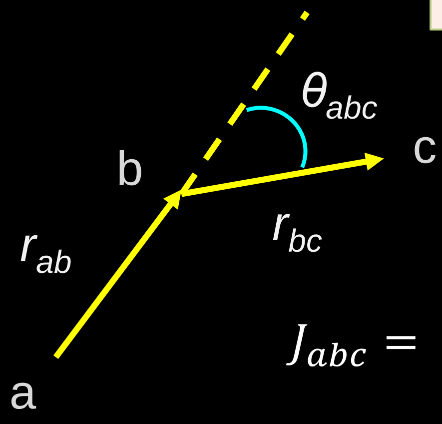


Ising-like hamiltonians

Davide Nicotra
PhD student

Goal: Map the tracking problem to an Ising-like hamiltonian

$$E = -\frac{1}{2}\left[\sum_{abc} J_{abc}\, s_{ab} s_{bc} - \alpha\left(\sum_{b\neq c} s_{ab} s_{ac} + \sum_{a\neq c} s_{ab} s_{cb}\right) - \beta\left(\sum_{a,b} s_{ab} - N\right)^2\right]$$

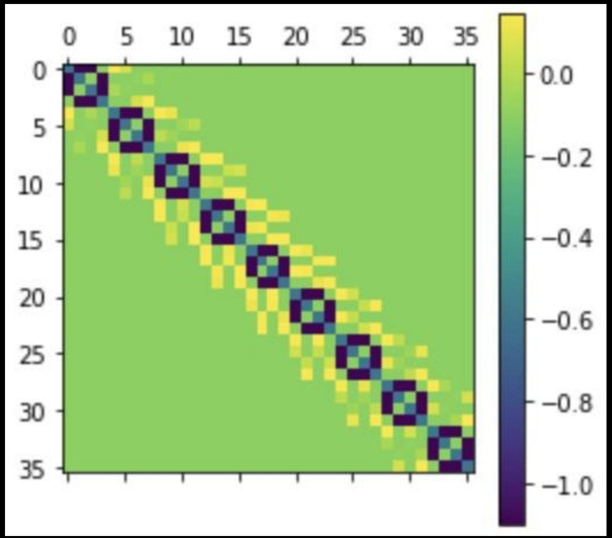


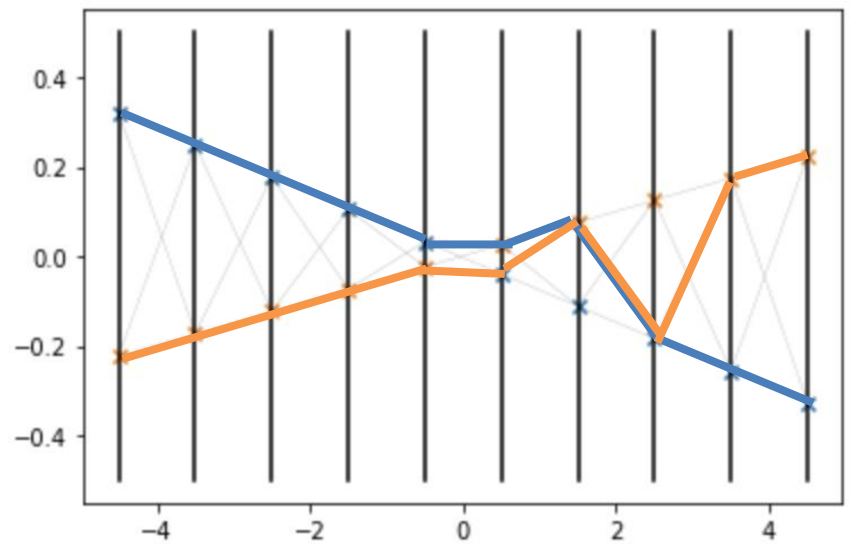
$$J_{abc} = \frac{\cos^{\lambda}\theta_{abc}}{r_{ab} + r_{bc}}$$

$$E = -\frac{1}{2}\left[\sum_{a,b}\left(W_{ab}^{reward} - W_{ab}^{penality}\right) s_{ab} + \sum_{a,b,c}\left(U_{abc}^{reward} - U_{abc}^{penality}\right) s_{ab} s_{bc}\right]$$

$$Us = W$$

$$s = U^{-1}W$$





Charged particle tracking with quantum annealing optimization
2021, Quantum Machine Intelligence (2021) 3: 27

Robentrost et al, 2019

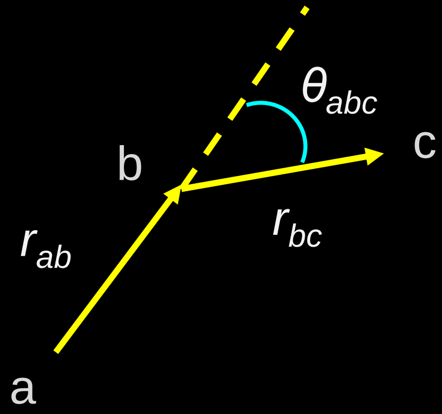
Tracks from simulation → QUBO construction → matrix inversion (HHL)

Ising-like hamiltonians

Dr. Miriam Lucio Martinez
postdoc

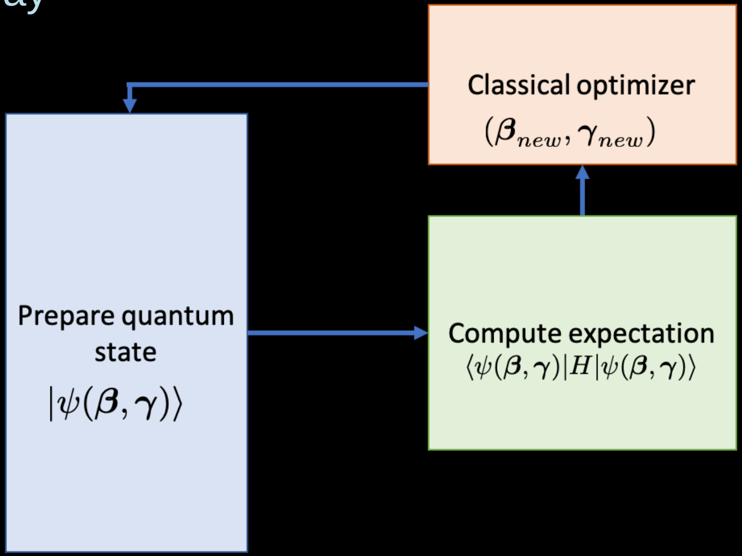
Goal: Map the tracking problem to an Ising-like hamiltonian

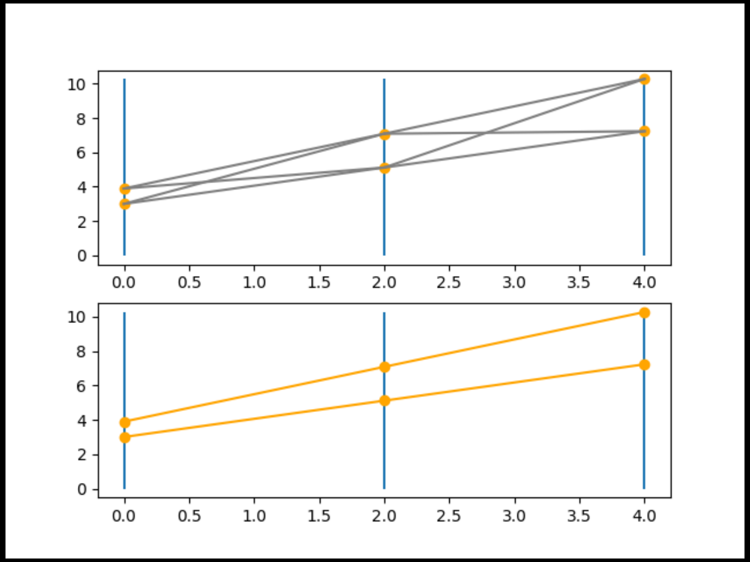
$$H_p = -\frac{1}{2}\left[\sum_{abc} J_{abc}\, s_{ab} s_{bc}\right] \qquad J_{abc} = \frac{\cos^{\lambda}\theta_{abc}}{r_{ab} + r_{bc}}$$



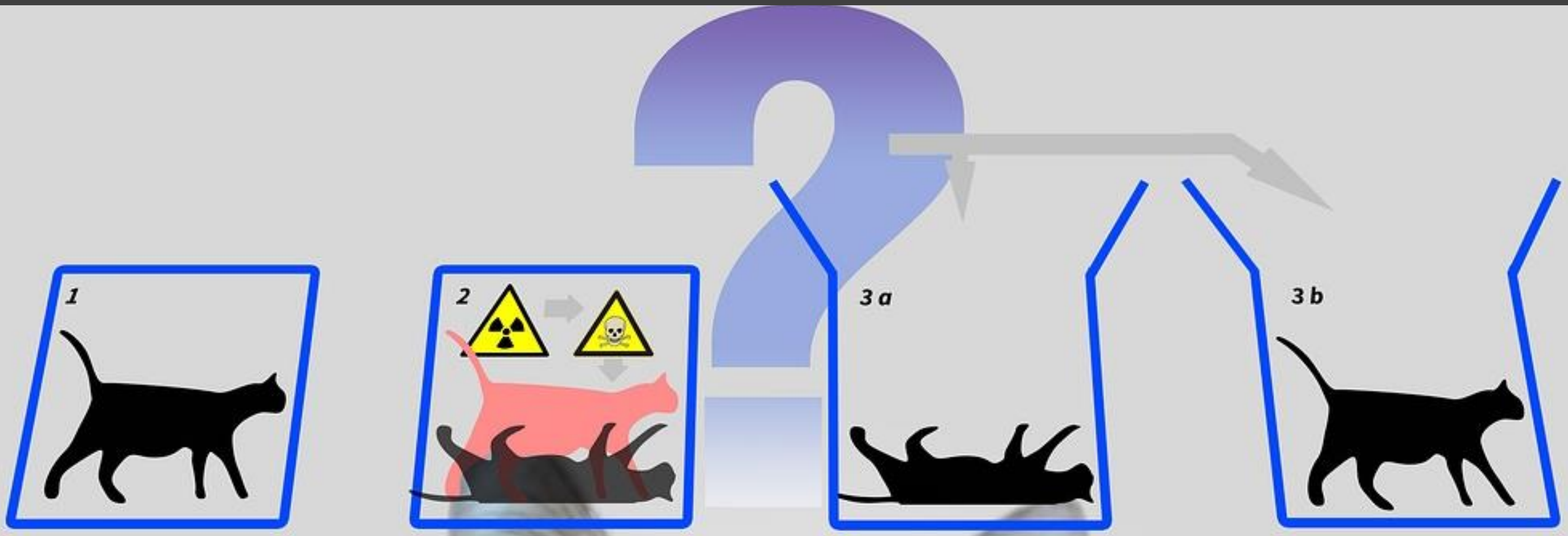
Approximating the adiabatic pathway

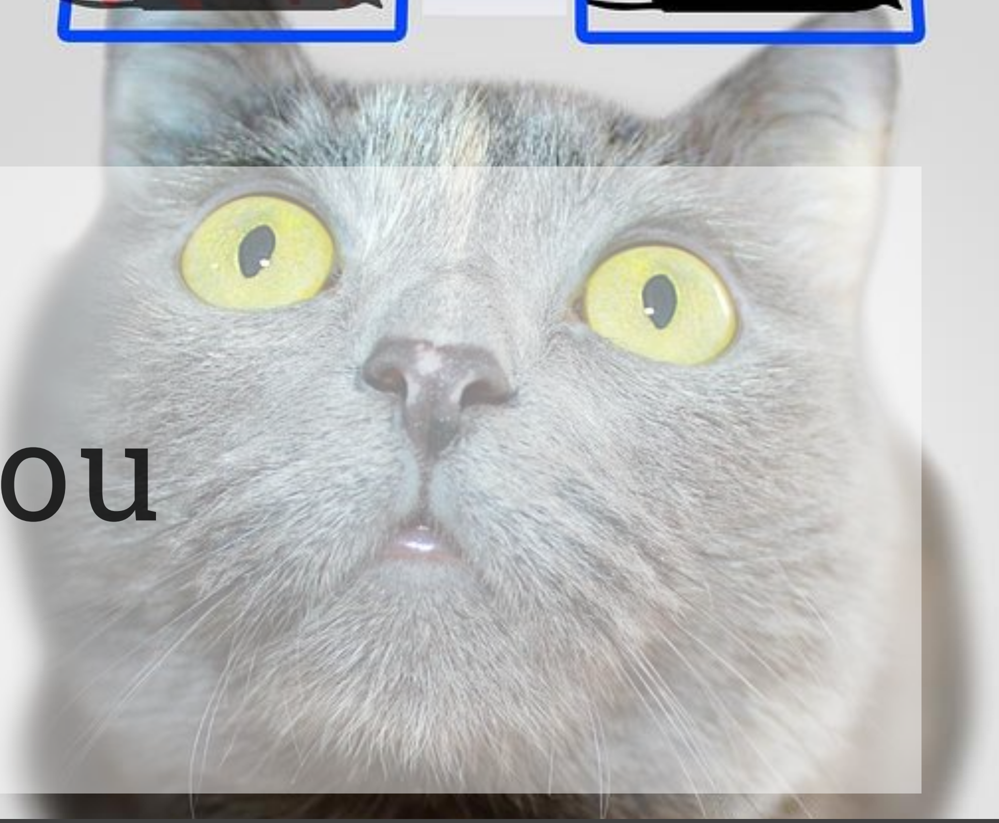
$$\left\langle\psi\middle| e^{-i\gamma H_p}\, e^{-i\beta H_B} \middle|\psi\right\rangle$$





Tracks from simulation → QUBO construction → QAOA algorithm





Thank you