Classic and Quantum Machine Learning Polarization Discrimination in Vector Boson Scattering (VBS)

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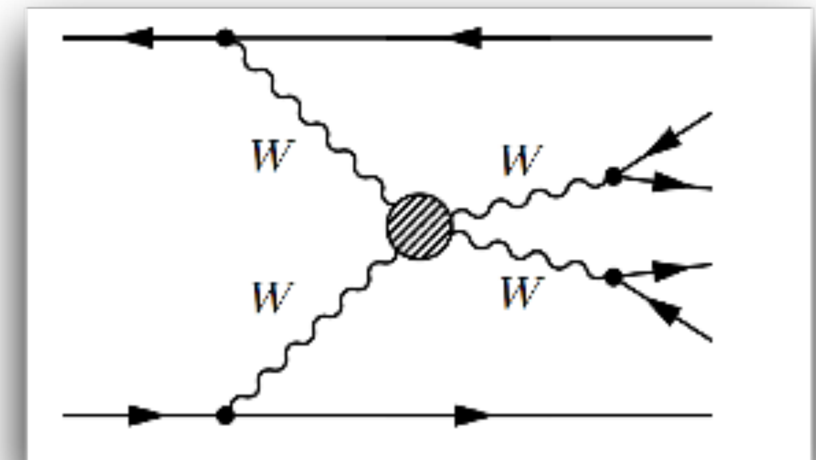
Outline

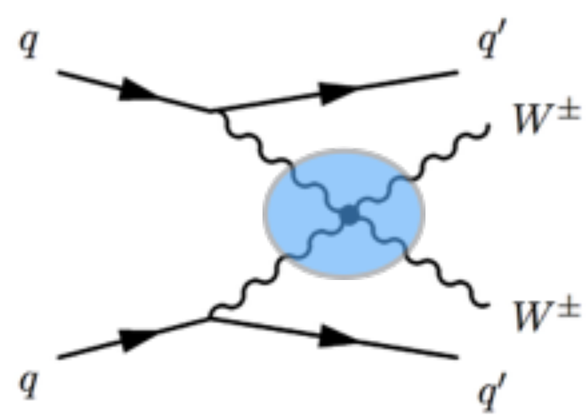
1. Standard Model & Vector Boson Scattering
2. Polarisation Discrimination with Machine Learning
3. Quantum Approach to VBS
4. Conclusions

Vector Boson Scattering @ LHC

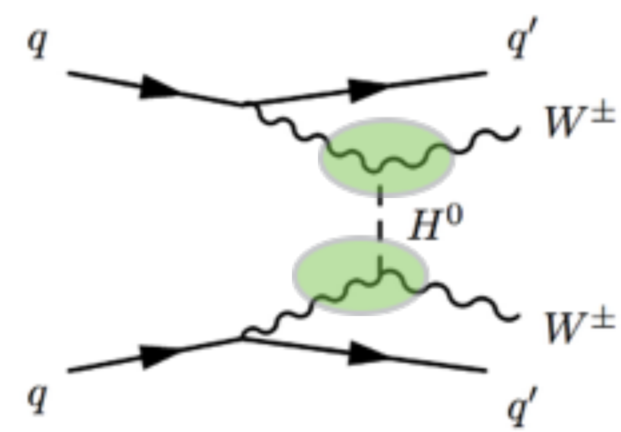
- The existence of a scalar boson (the Higgs) is sufficient to prove the correctness of the mechanism which gives masses to bosons (the Higgs mechanism) but not sufficient to prove that the same Higgs mechanism is responsible for the fermion masses



Quartic Gauge Coupling

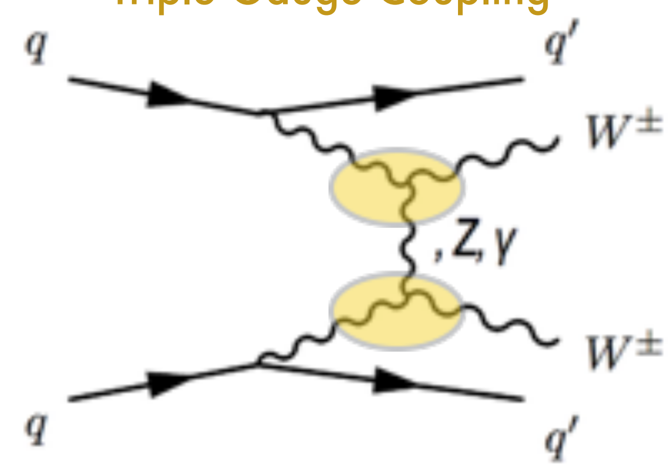


Higgs coupling to vector boson



- Unitarity at high energies requires presence of the SM Higgs boson
- Sensitivity grows with energy of vector bosons
- Self-interaction of heavy gauge bosons
- Search for anomalous quartic-gauge-boson couplings

Triple Gauge Coupling

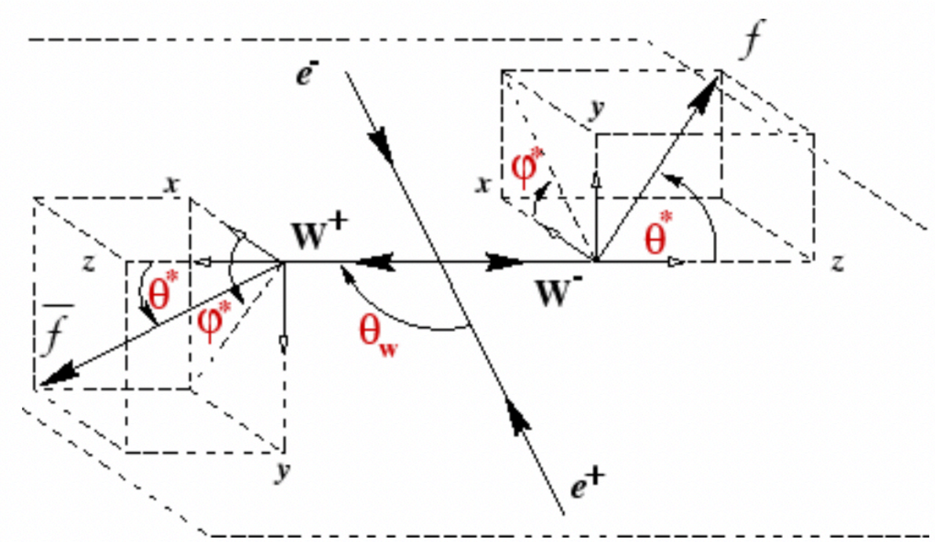


[Ref 1, $W^{\pm}W^{\pm}$ VBS at 13 TeV: Overview, PRL 120, 081801 (2018) Ref2, https://arxiv.org/abs/1906.03203]

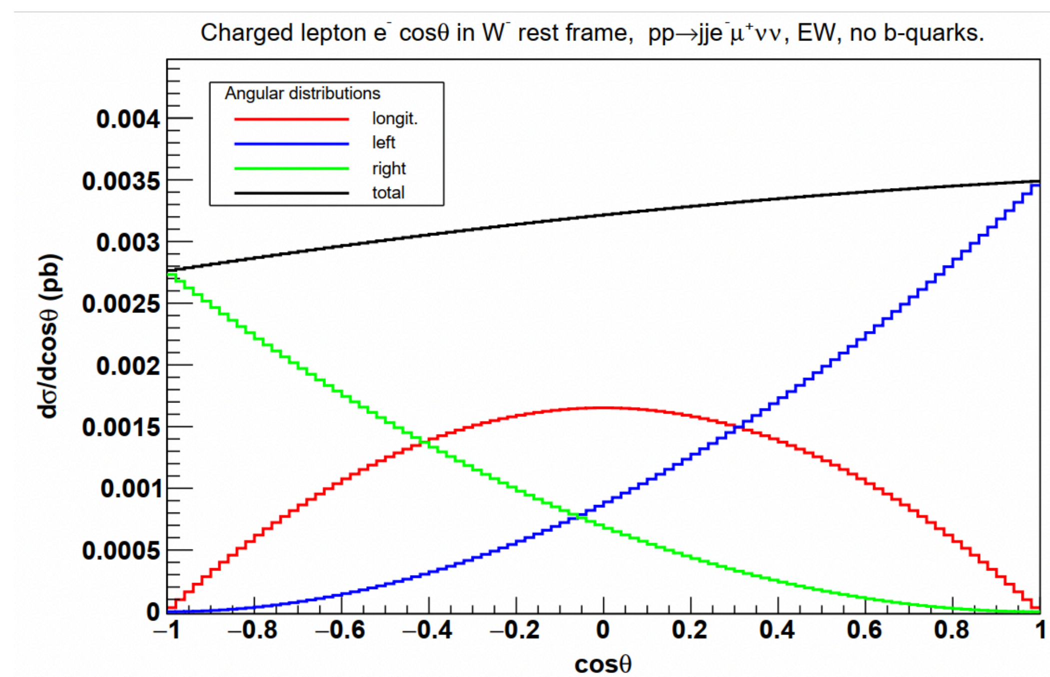
VBS Polarisation Focus

- The cross-section and angular distribution of longitudinal polarisations are particularly sensitive to beyond standard model (BSM) physics
- Boson polarisation can be measured as angular distributions of particles produced in the decay process [1]
- The differential cross-section with <u>no lepton cuts</u> for $W^{\pm} \rightarrow l^{\pm}\nu$ is:

$$\frac{1}{\sigma}\frac{d\sigma}{d\cos\theta}(W^{\pm} \rightarrow l^{\pm}\nu) = \frac{3}{4} f_0 \sin^2\theta + \frac{3}{8} f_R (1 \pm \cos\theta)^2 + \frac{3}{8} f_L (1 \mp \cos\theta)^2$$



- where f_0, f_R, f_L are W polarisation fractions
- θ is the lepton polar angle in the **W rest frame** wrt W direction in the lab. frame



- In the W reference frame and ultra-relativistic limit, solving for the longitudinal component of the neutrino one finds:

$$\underbrace{\left(p_{\ell L}^2 - E_\ell^2\right)}_{a} p_{\nu L}^2 + \underbrace{\left(m_W^2 p_{\ell L} + 2 p_{\ell L} \vec{p}_{\ell T} \vec{p}_{\nu T}\right)}_{b} p_{\nu L} + \underbrace{\frac{m_W^4}{4} + (\vec{p}_{\ell T} \vec{p}_{\nu T})^2 + m_W^2 \vec{p}_{\ell T} \vec{p}_{\nu T} - E_\ell^2 \vec{p}_{\nu T}^{\,2})}_{c} = 0$$

$$\Rightarrow \quad \boxed{p_{\nu L} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}}$$

[[1]A. Ballestrero, E. Maina, and G. Pelliccioli, W boson polarization in vector boson scattering at the LHC, JHEP 03 (2018)]

Polarisation Separation with Machine Learning

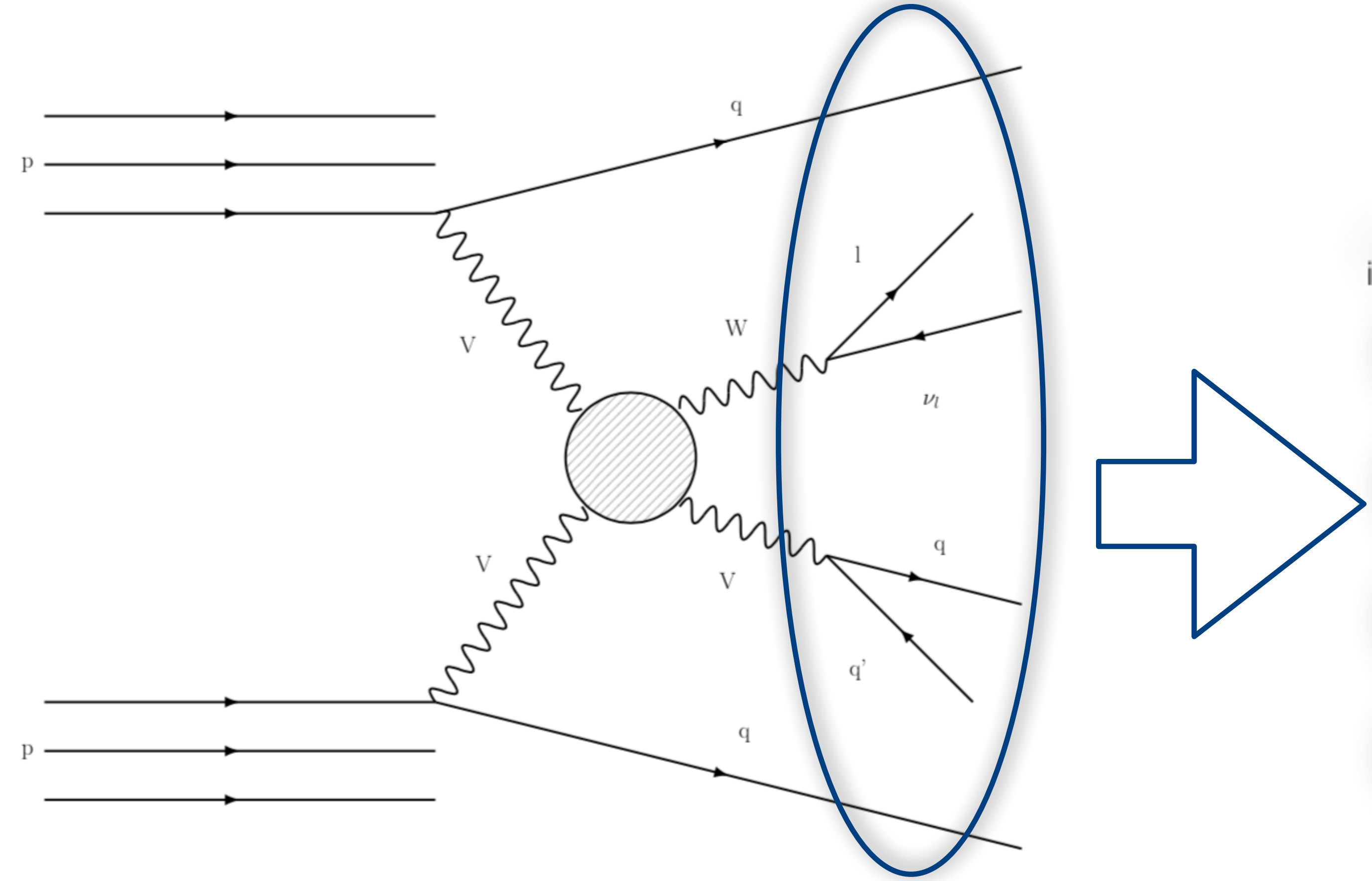
- A dense neural network (NN) is built for binary classification of the events with the following label:
  - Events with first solution closer to truth solution (1)
  - Events with second solution closer to truth (0)
- Training of the NN is made on unpolarised and polarised sample using all kinematic variables of the event coming from MC generator (PHANTOM)

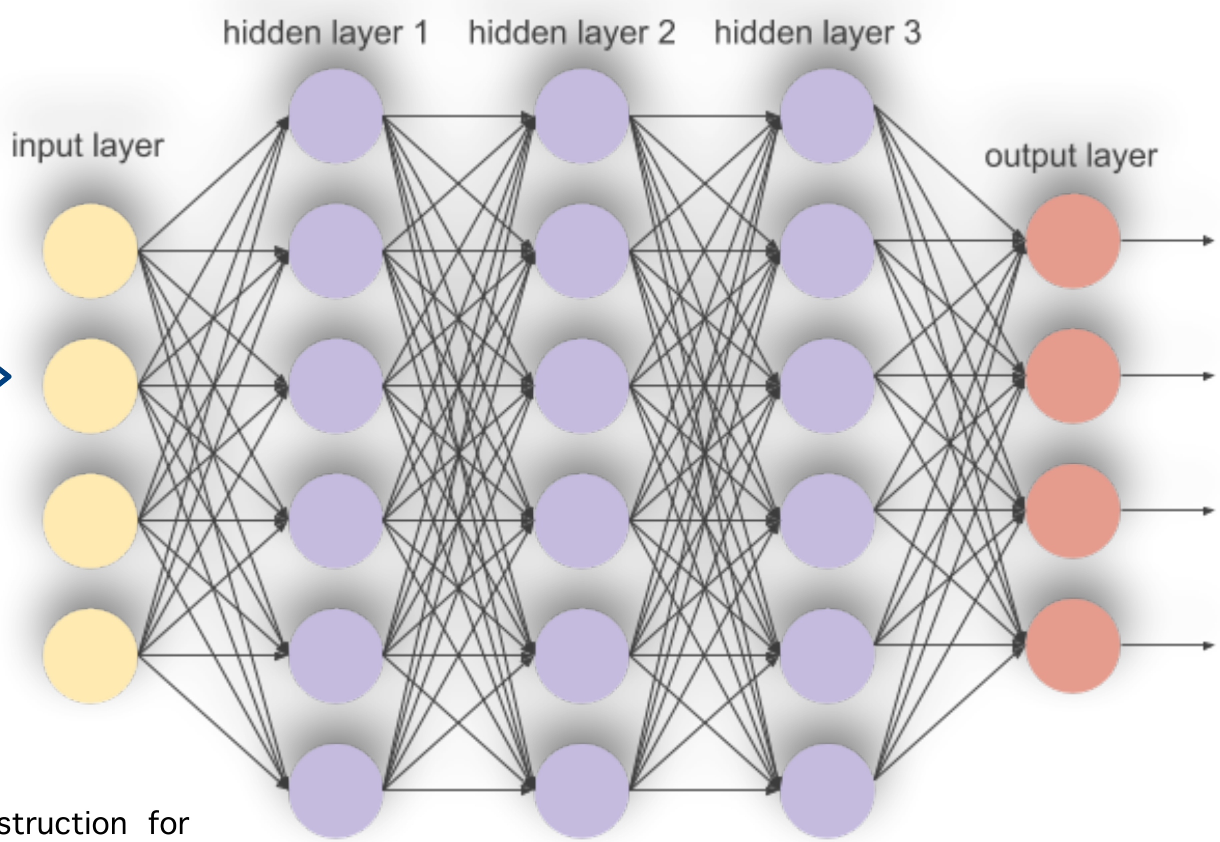
Hyper-parameters optimised:

- Number of layers
- Number of nodes
- Training batch size

Fixed parameters:

- Learning-rate, decay-rate

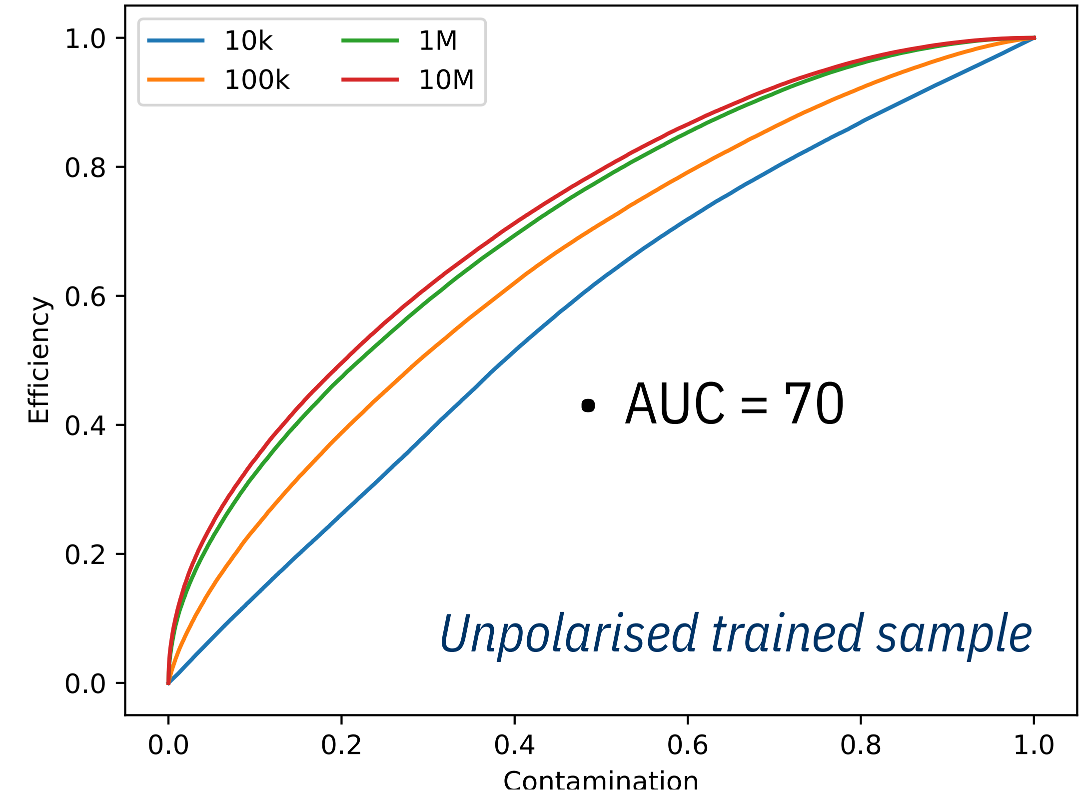


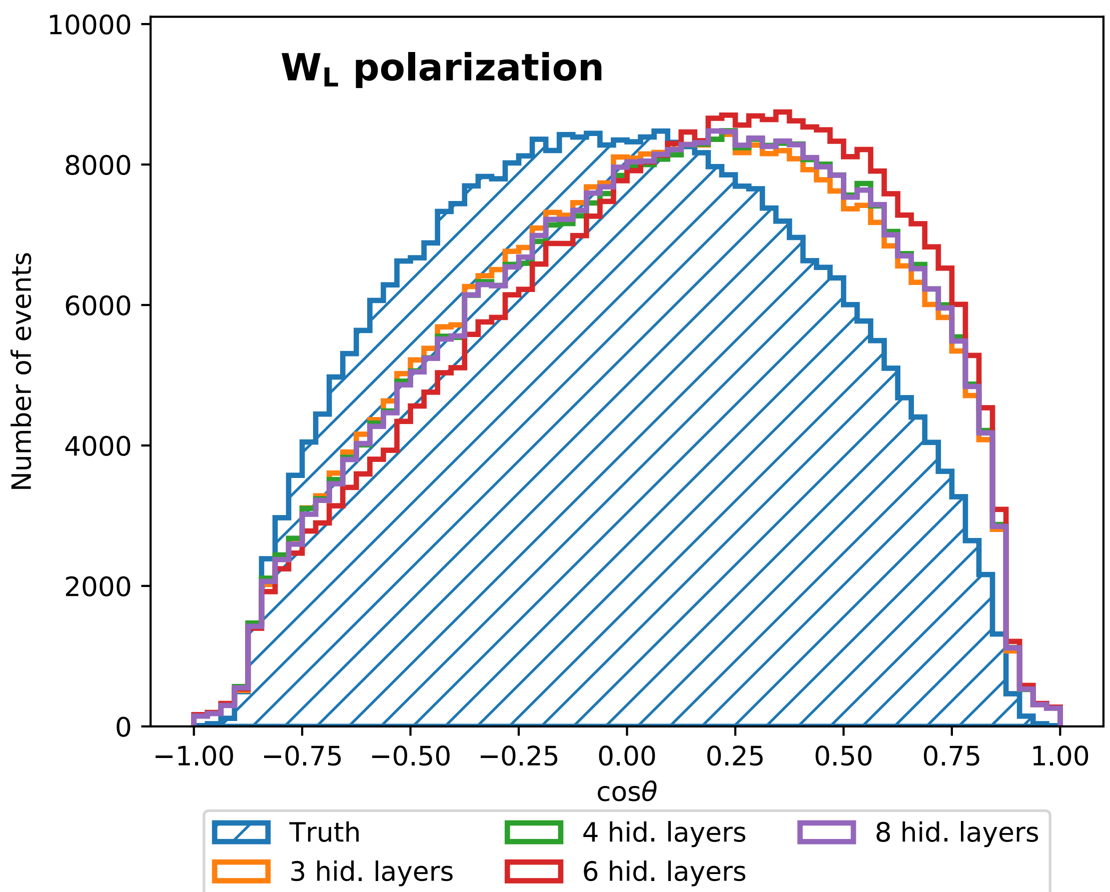


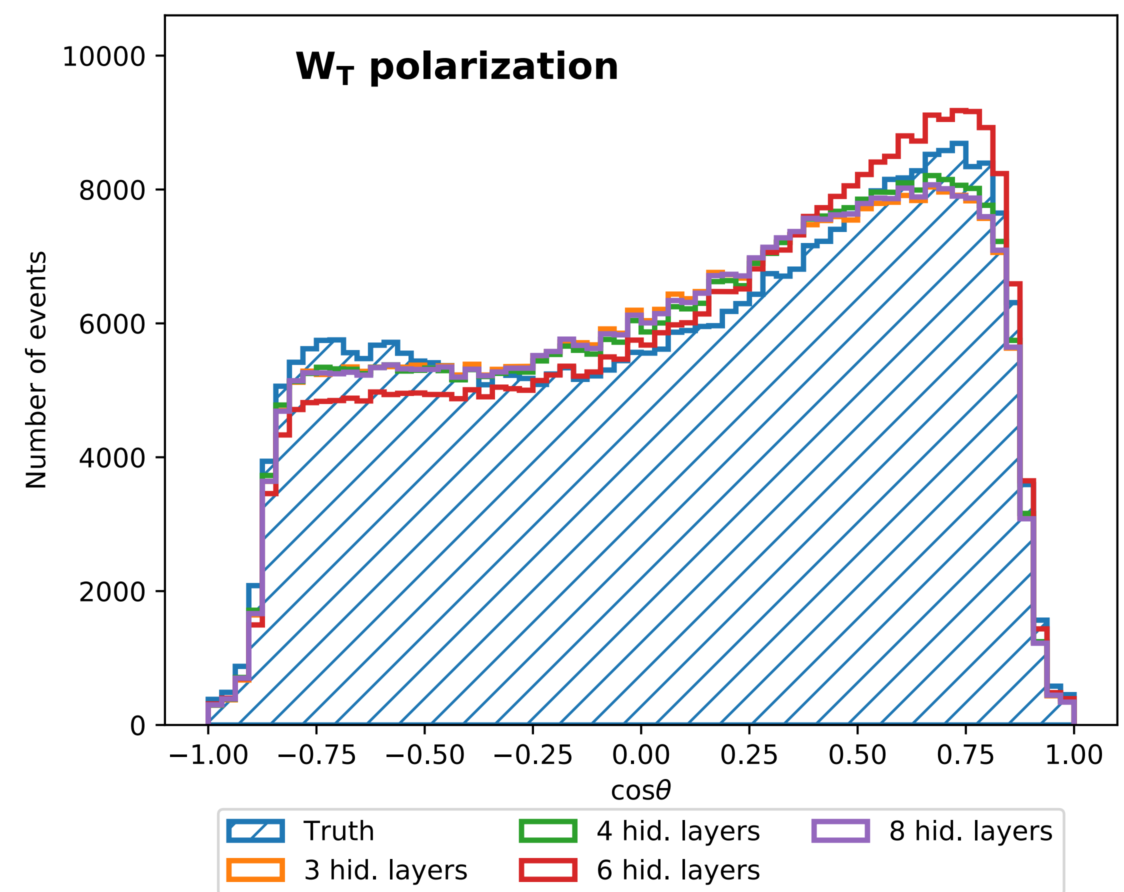
[M Grossi et all., Comparing Traditional and Deep-Learning Techniques of Kinematic Reconstruction for polarisation Discrimination in Vector Boson Scattering, arXiv 2008.05316, under publication on EPJC]

Binary Classification - Angular Distribution

- <u>Evaluation</u> is made applying the trained model on polarised sample to get $p_{\nu L}$ and E_ν in the laboratory frame
- Lepton momentum is boosted into re-constructed W rest frame, defined by the vector sum of neutrino and lepton momentum.
- Plot of transverse and longitudinal distribution on top of truth angular distribution

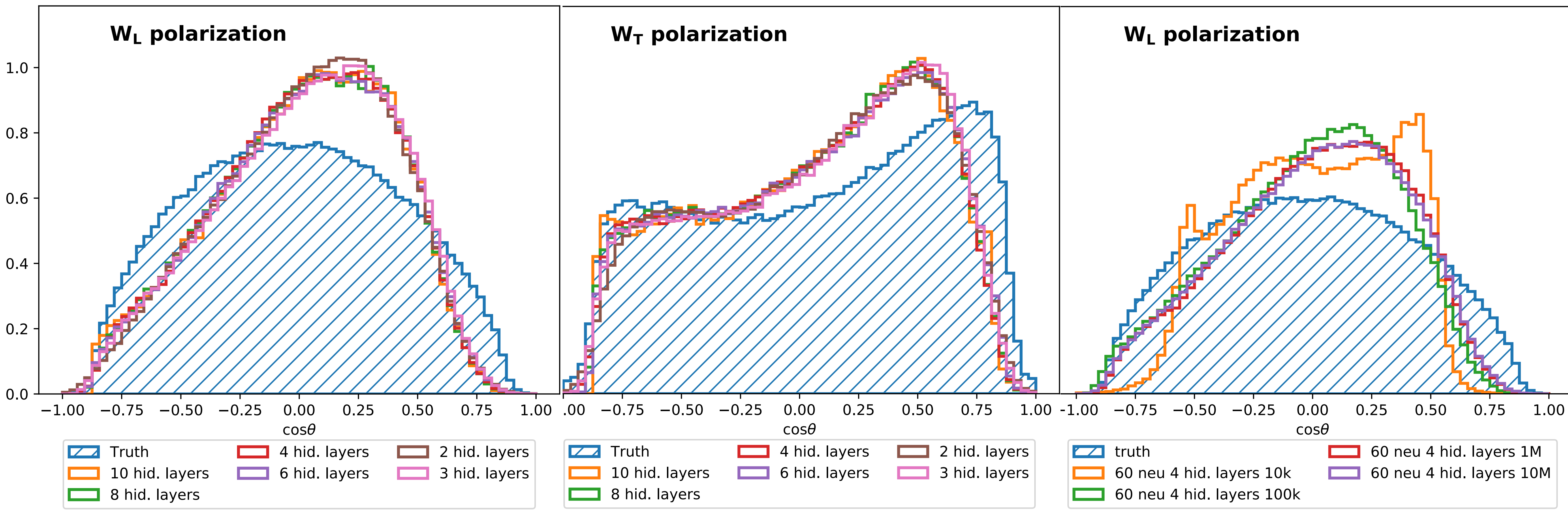






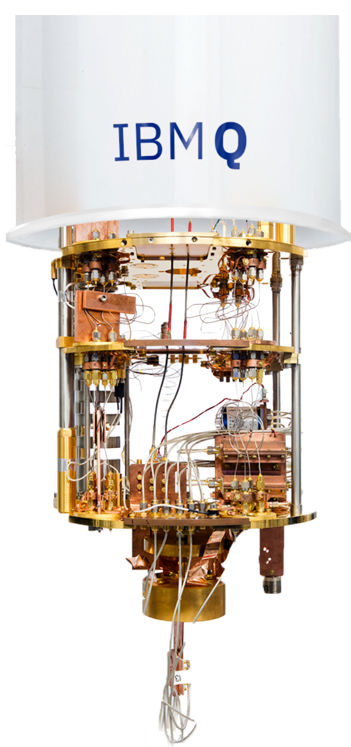
Regression - Angular Distribution

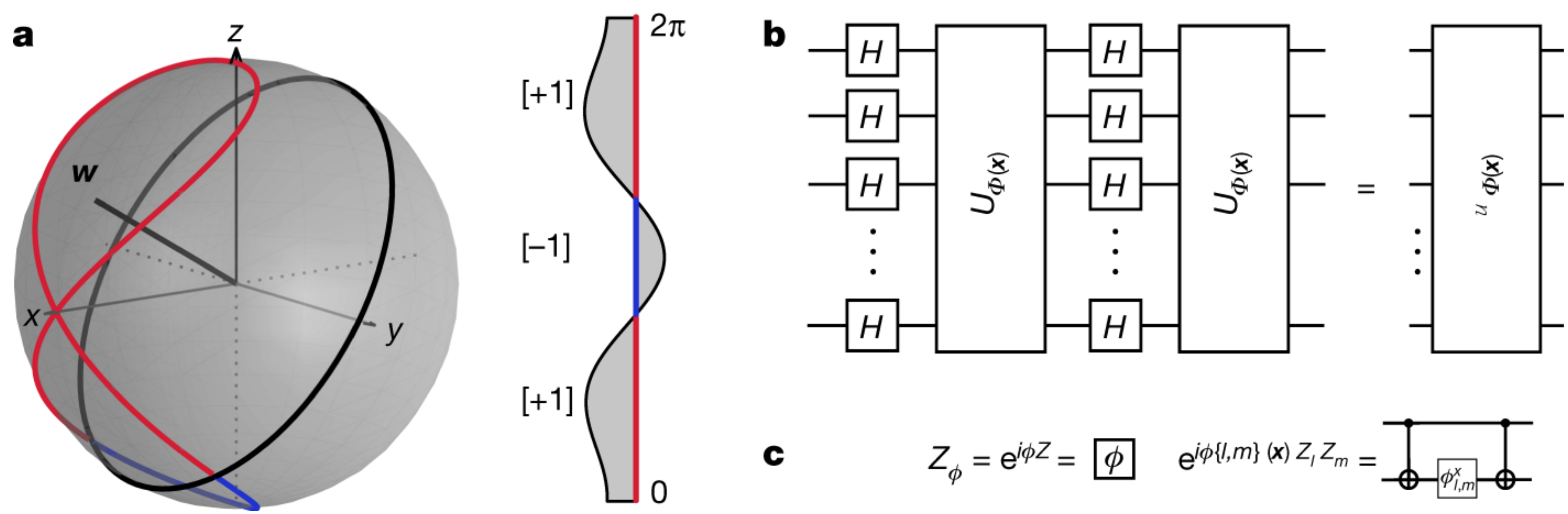
- NN training to determine directly the reconstructed angular distributions of the lepton in *W* rest frame, with respect to the *W* direction in the laboratory frame and as a function of different training dataset sizes.



Quantum Approach to VBS

- Support vector machines (SVM) address the problem of supervised learning through the construction of a classifier.
- Here we are evaluating two strategies to design a quantum SVM [1]:
  Quantum Kernel Estimator and the **Quantum Variational Classifier**.
- How it work: use data that is provided classically and encodes it in the quantum state space through a quantum feature map
- A quantum feature map nonlinearly maps a classical datum x to a quantum state $|\Phi(\mathbf{x})\rangle\langle\Phi(\mathbf{x})|$, a vector in the Hilbert space of density matrices. Support vector machine classifiers find a hyperplane separating each vector $|\Phi(\mathbf{x}_i)\rangle\langle\Phi(\mathbf{x}_i)|$ depending on its label, supported by a reduced amount of vectors (the so-called support vectors). A key element of the feature map is not only the use of quantum state space as a feature space but also the way data are mapped into this high dimensional space.

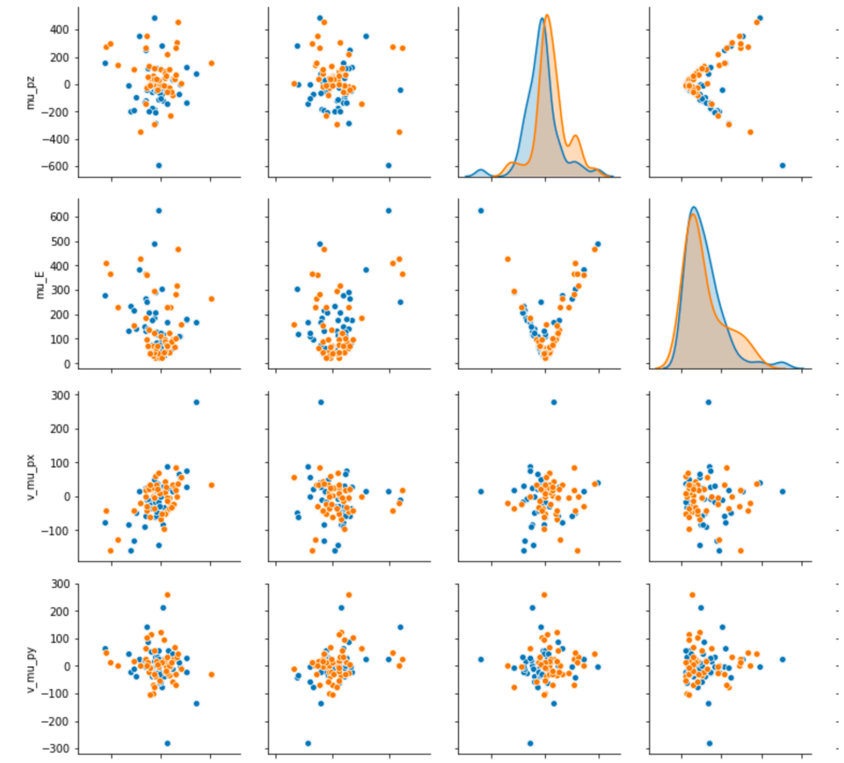


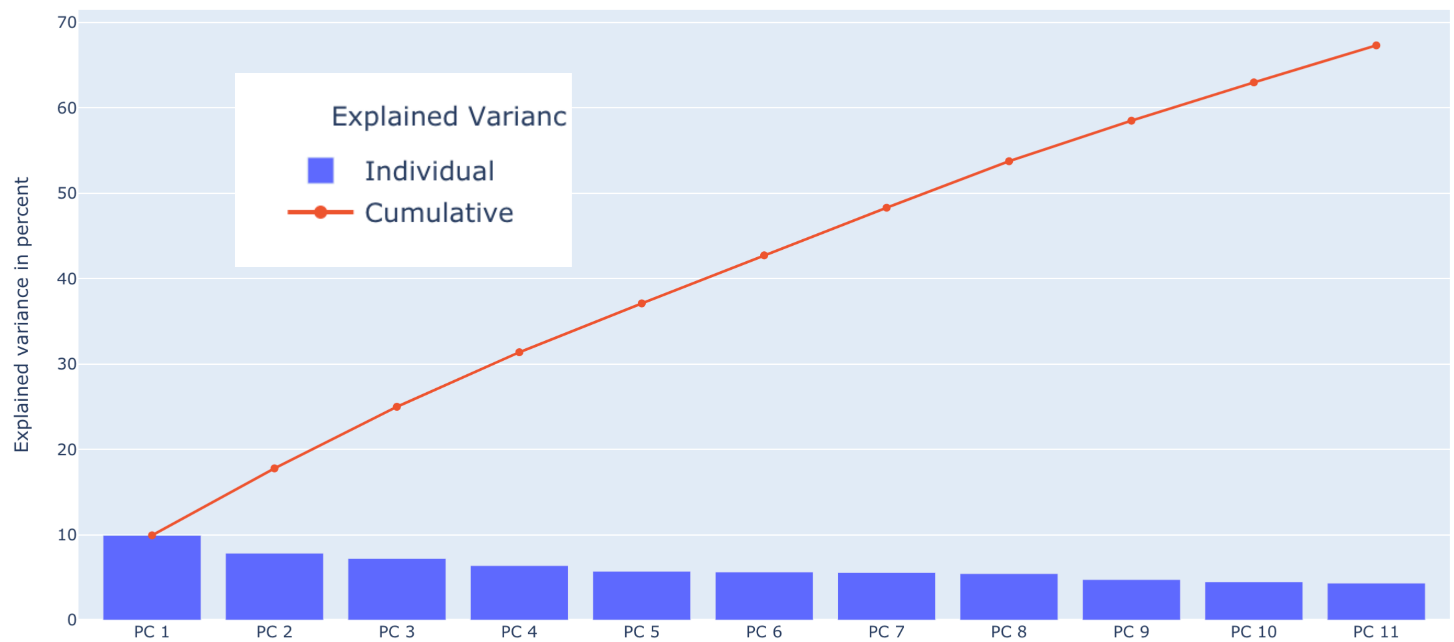


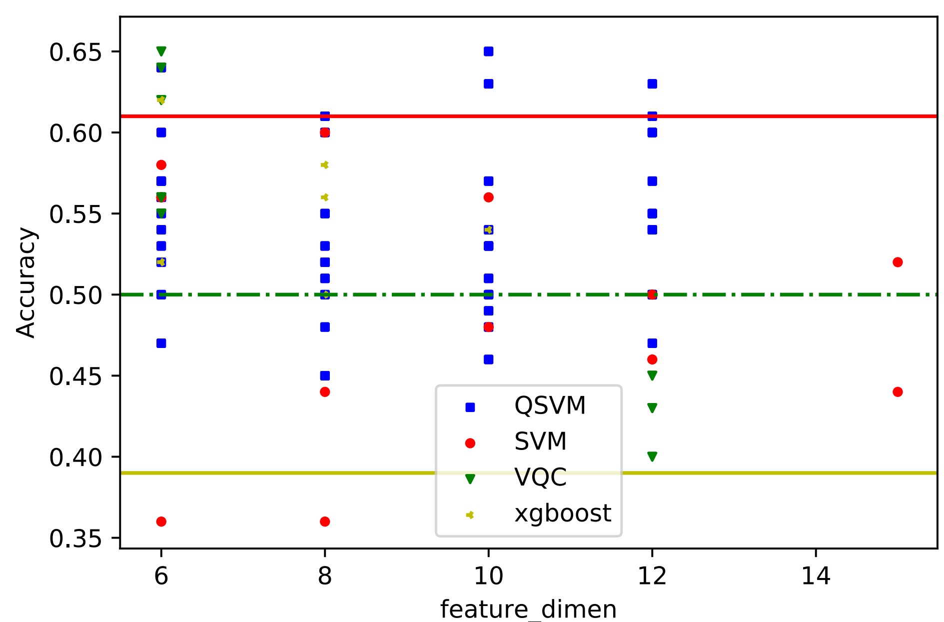
[1] Havlicek et al. Nature 567, 209-212 (2019).

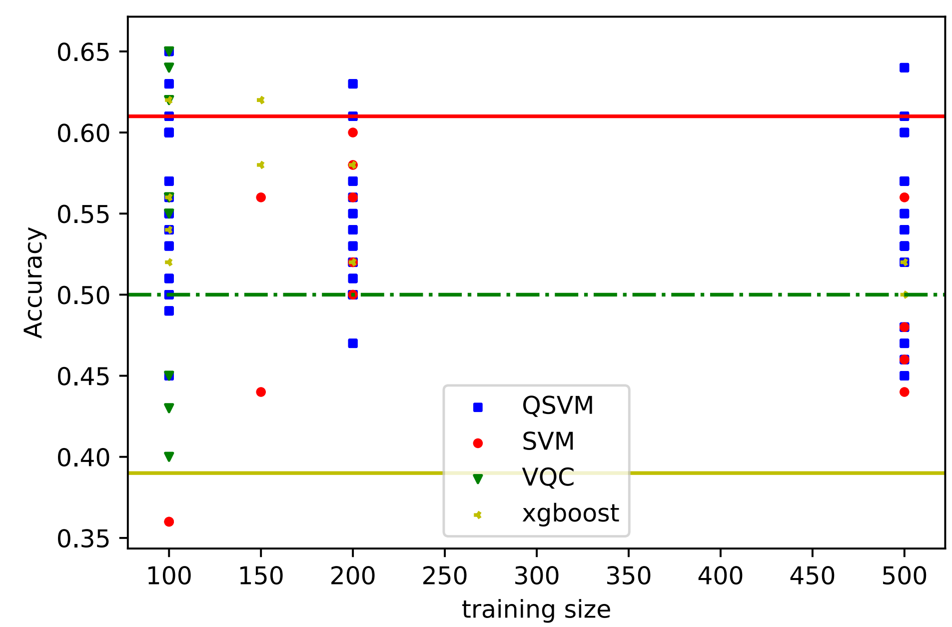
Dimensionality Reduction and Preliminary Results

- Given the current status of NISQ device we are limited in the number of features to map for our problem. To reduce the dimension of this space we apply the PCA analysis
- We need to find balance between number of PCA and total variance explained









Conclusion

- VBS measurements provide an important probe of a previously untested sector of the standard model
- We evaluated neural network approaches to determine polarisation separation feasibility and W boson kinematic reconstruction that could be useful in another kinematic-like processes
- A parallel analysis technique making use of innovative quantum technology has been tested. Some Quantum Machine Learning algorithms, *e.g. quantum SVM, quantum PCA, QGAN* are under investigation to set the boundary of current quantum computing technology in High Energy Physics field.

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