Presented by Saasha Joshi
July 31, 2025

INTRODUCTION TO QUANTUM MACHINE LEARNING

ABOUT ME

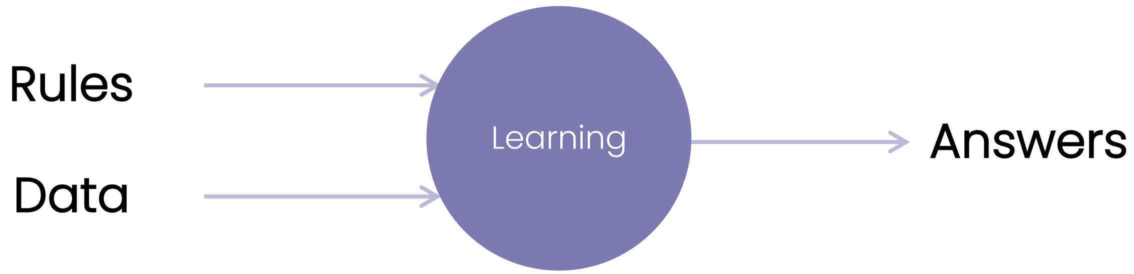
Staff Scientist in Quantum Computing at CMC Microsystems, Canada

- Research in QML and quantum software development.
- MSc degree in Computer Science with a focus on QC from the University of Victoria.
- Actively involved in open-source development and educating and mentoring students.

CONTENT

MACHINE LEARNING

TRADITIONAL VS MACHINE LEARNING



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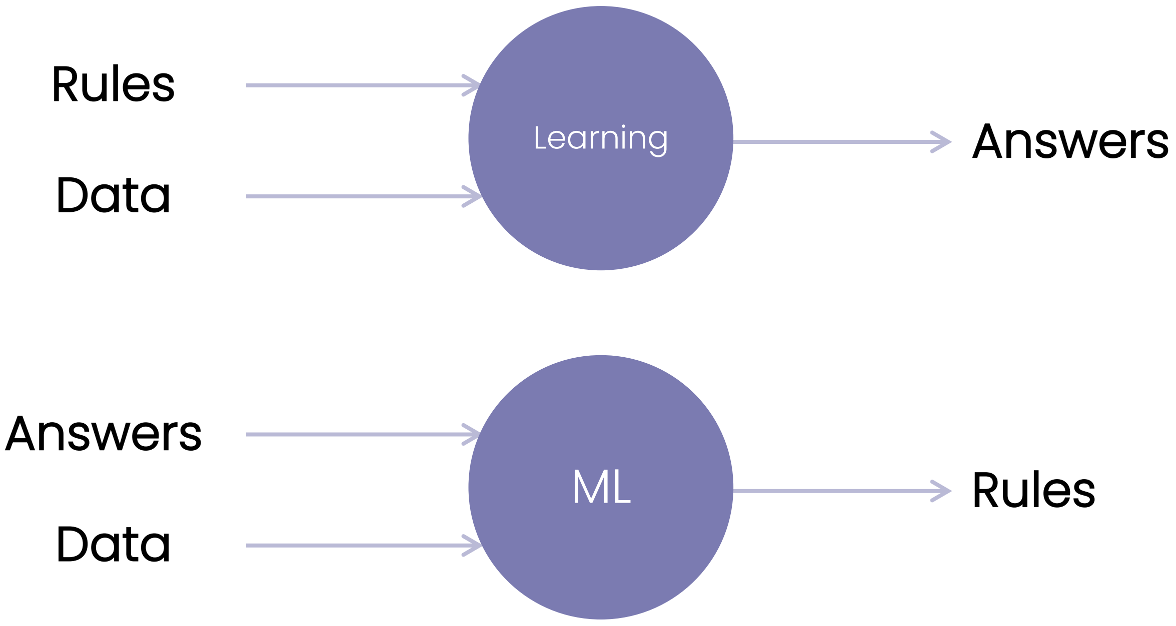
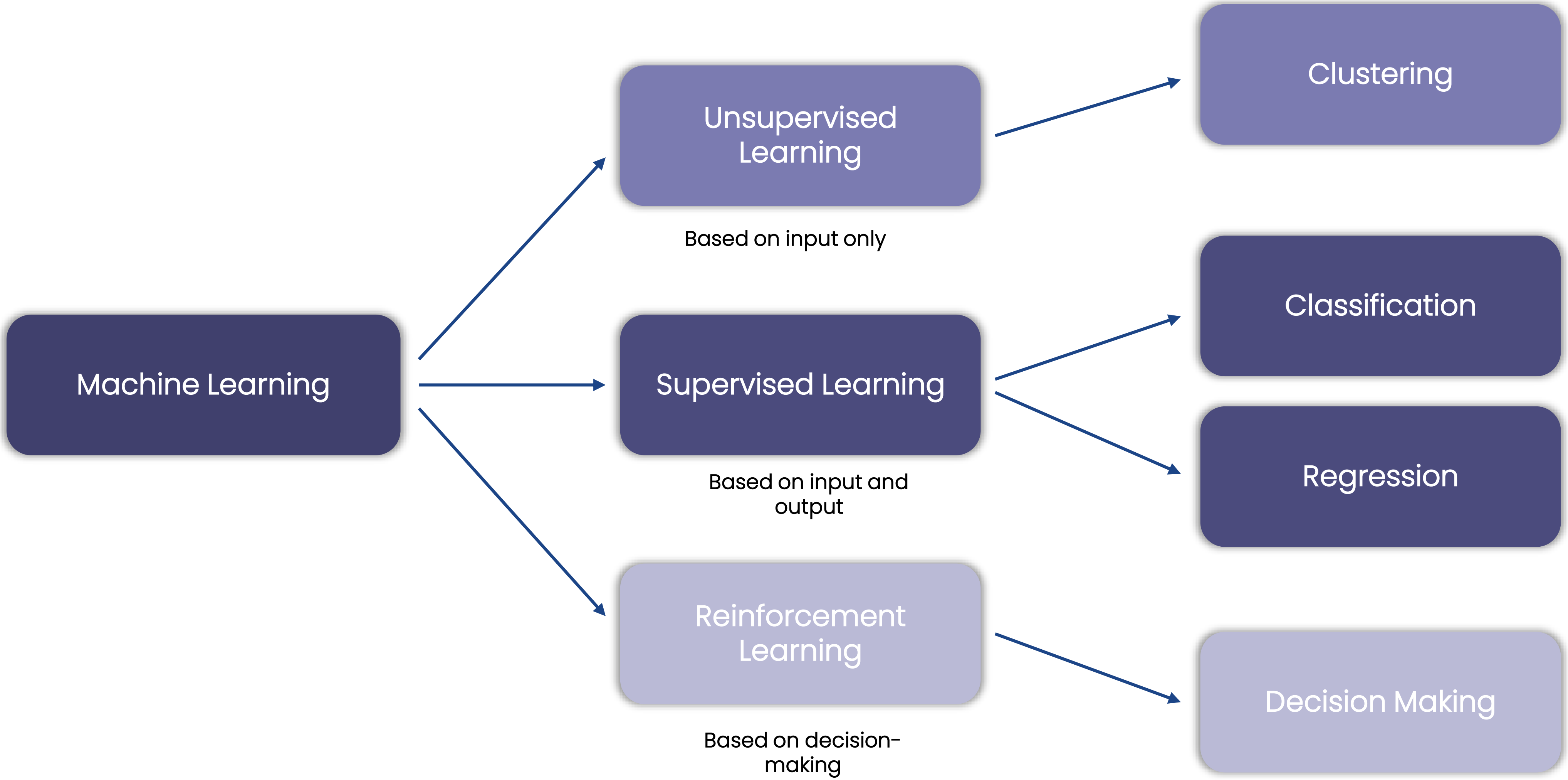


MACHINE LEARNING



SUPERVISED LEARNING: CLASSIFICATION

- The model helps in the classification of unseen data.

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Given training labelled data,

$$\chi = (x_i, y_i)$$

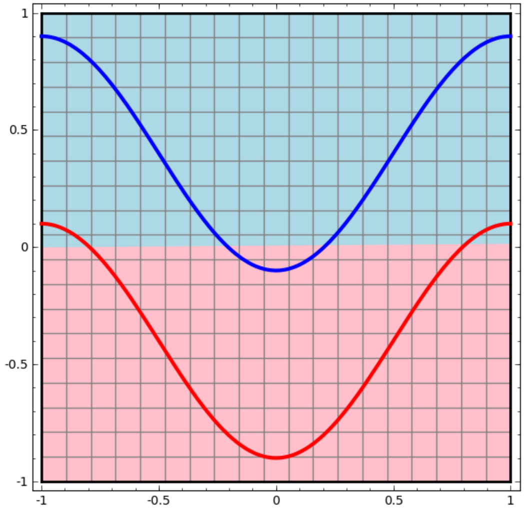
Supervised model learns a function that generalizes to unseen data.

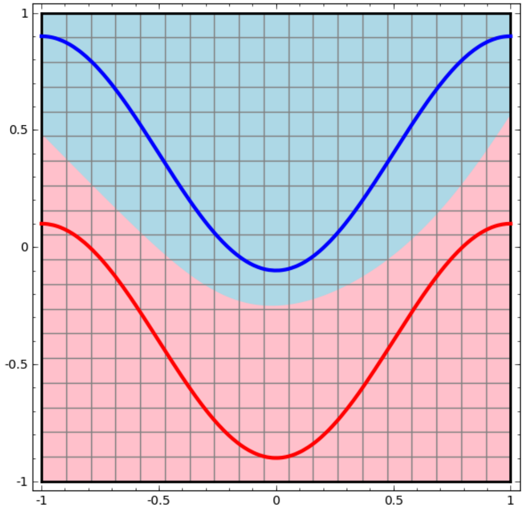
$$f : x \mapsto y$$

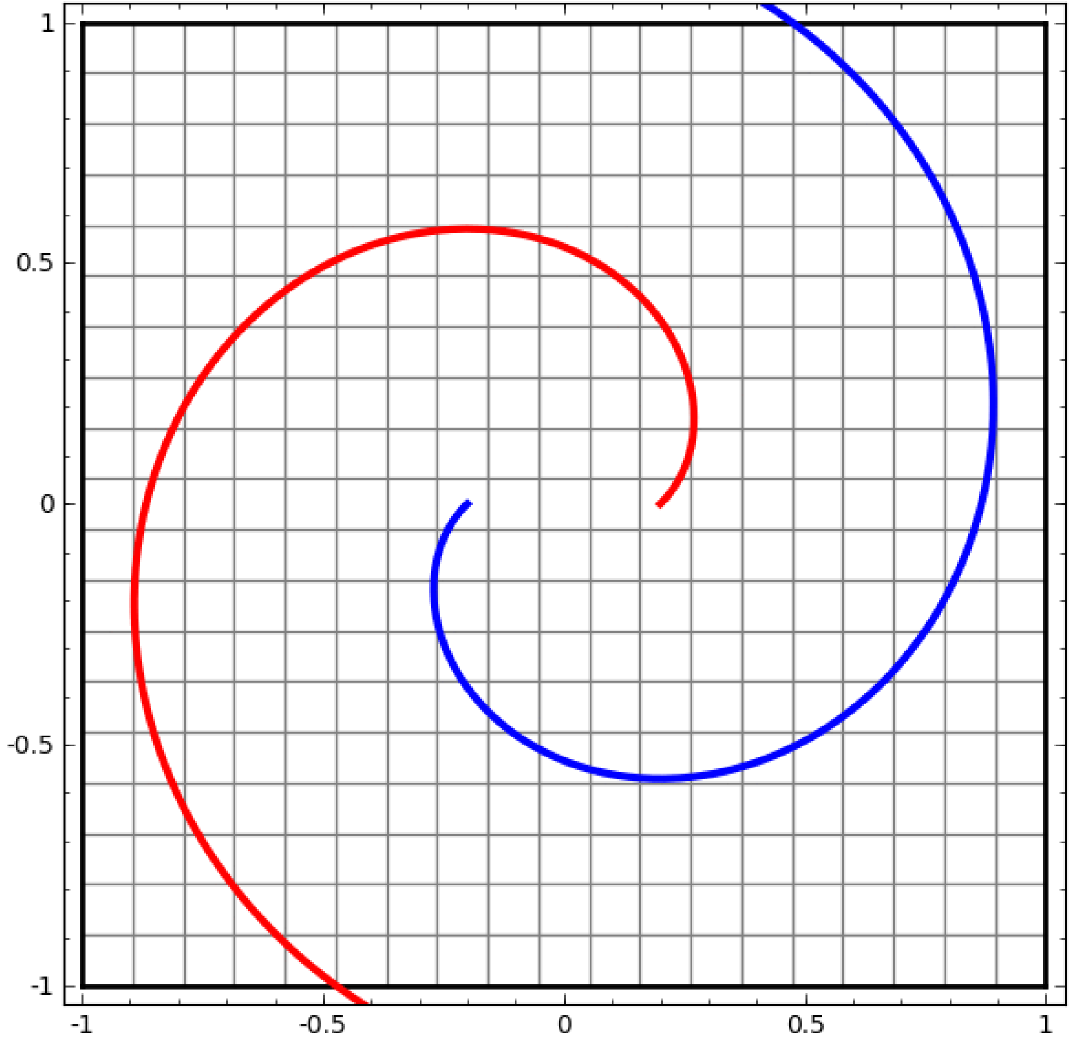
WHAT HAPPENS IF DATA IS NON-LINEAR?

Fix: High-dimensional feature mapping.

REAL WORLD DATA







Refer: https://colah.github.io/posts/2014-03-NN-Manifolds-Topology; https://cs.stanford.edu/people/karpathy/convnetjs//demo/classify2d.html; https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/img/spiral.1-2.2-2-2-2-2-2.gif

SUPPORT VECTOR MACHINE

- The data is non-linearly mapped to a high-dimensional space, called the ***feature space***, where a hyperplane is constructed to separate the samples.
- SVM utilizes ***kernels*** and the ***kernel trick*** to build this hyperplane.

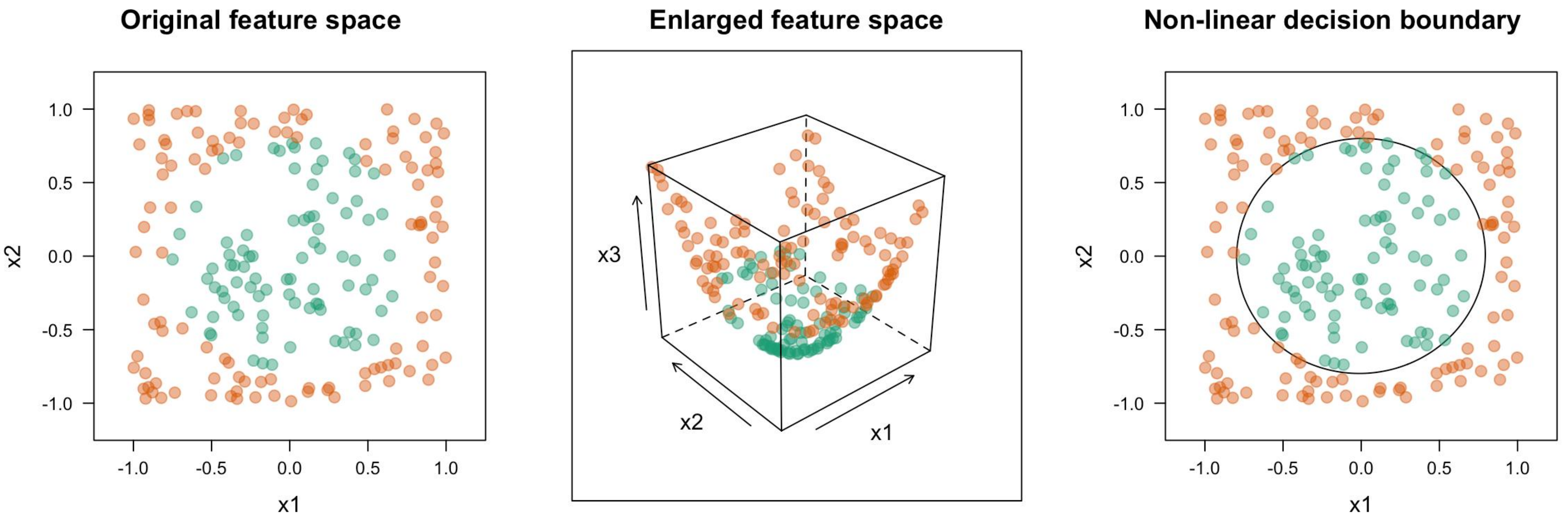
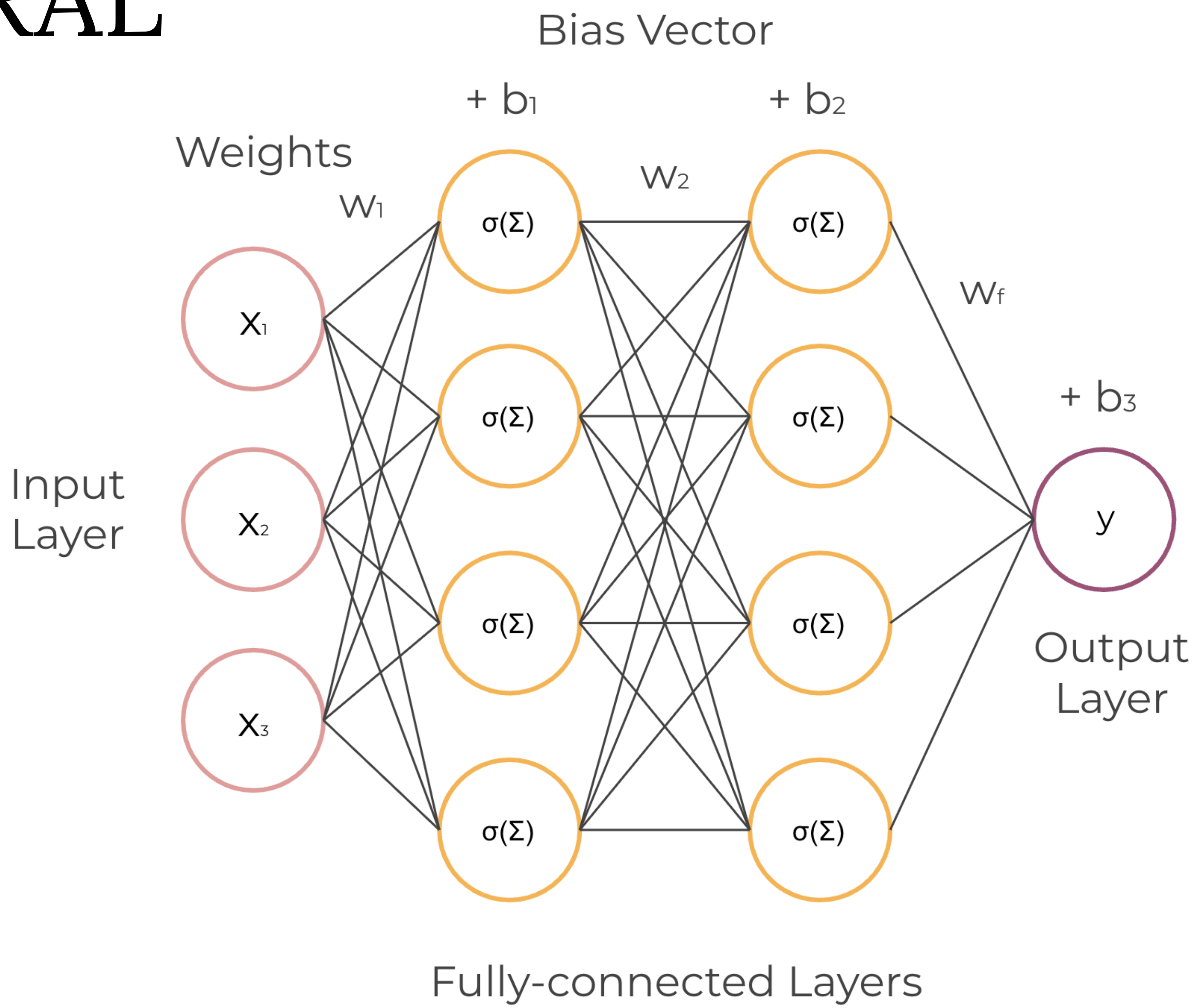


Image source: https://bradleyboehmke.github.io/HOML/svm.html

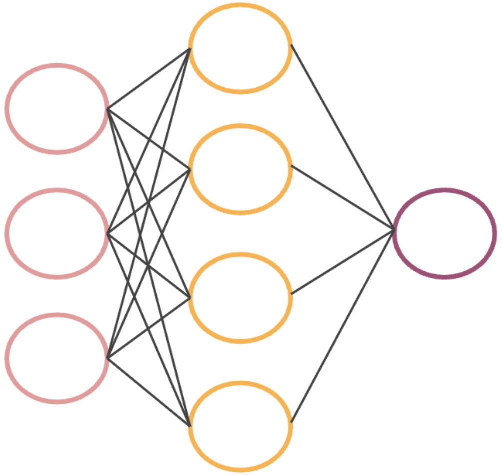
CLASSICAL NEURAL NETWORK

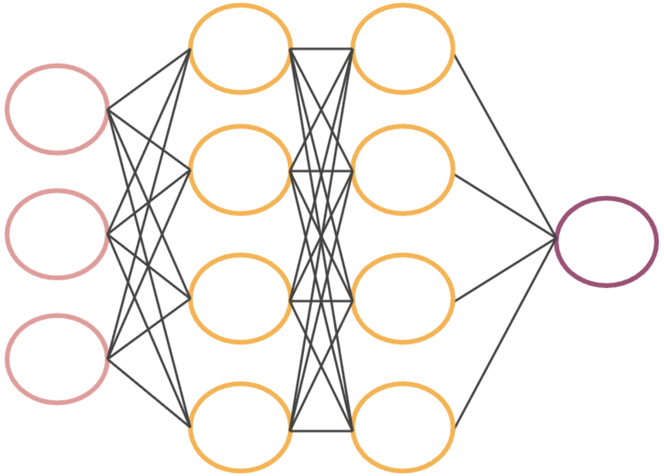
- With each layer, the neural network transforms the data, creating a new ***representation***.

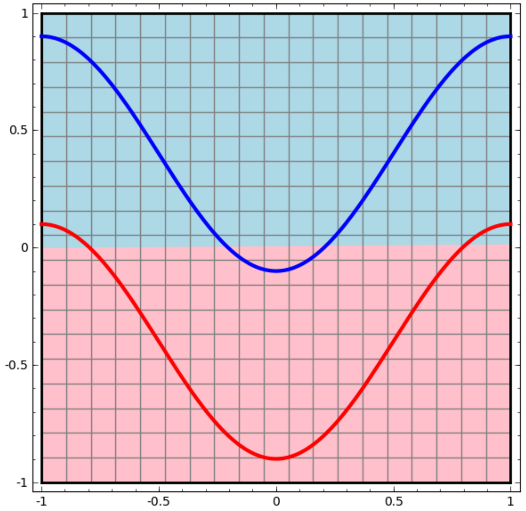


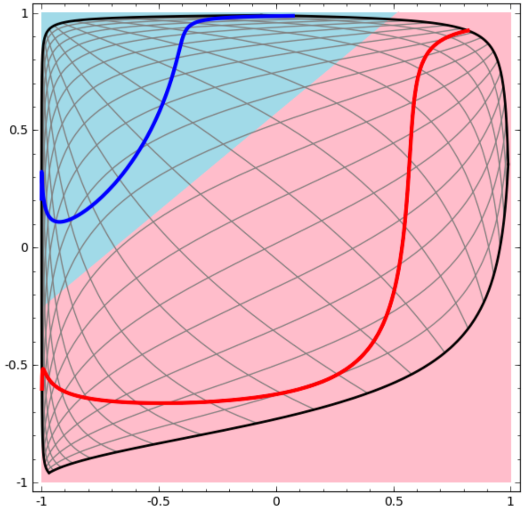
CLASSICAL NEURAL NETWORK

- With only one input layer, you can visualize the network as it attempts to separate the data by drawing a line through it.
- More hidden layers learn a representation such that the data is linearly separable.
- Each hidden layer corresponds to increase in the dimension.









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QUANTUM MACHINE LEARNING

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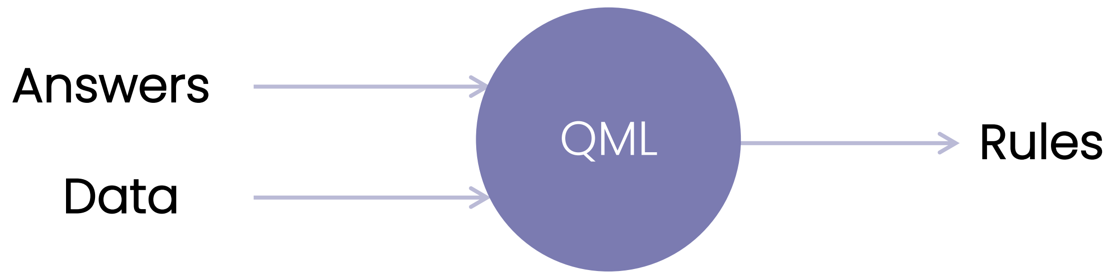
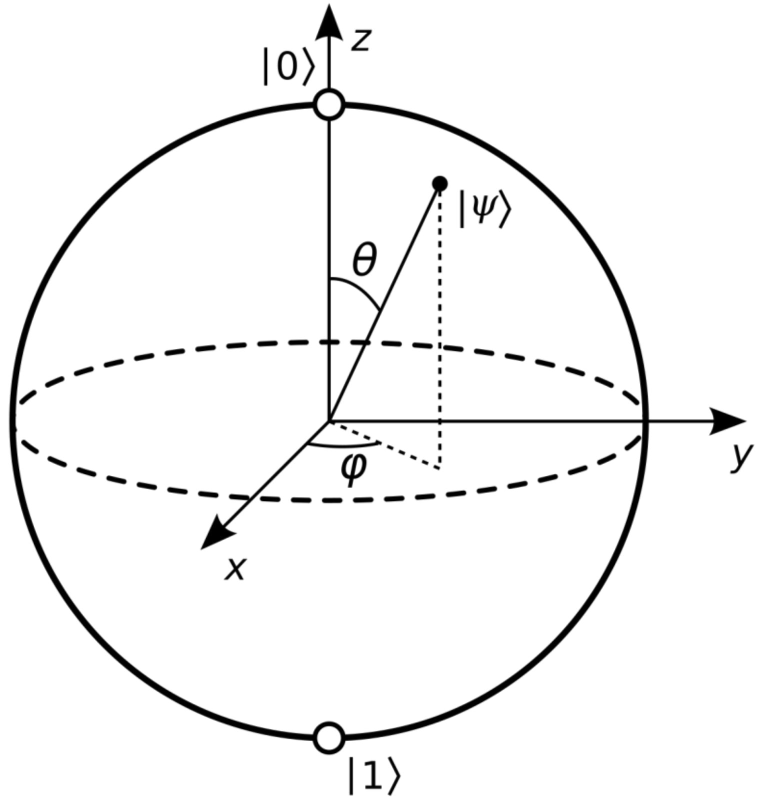
- QML lies at the intersection of quantum information and machine learning.
- It leverages quantum mechanical properties such as *superposition, entanglement, and interference*.



WE ALREADY HAVE A HIGHER-DIMENSIONAL SPACE!

- With quantum computers, we can map classical data to high-dimensional quantum states.

$$x \mapsto |\phi(x)\rangle$$



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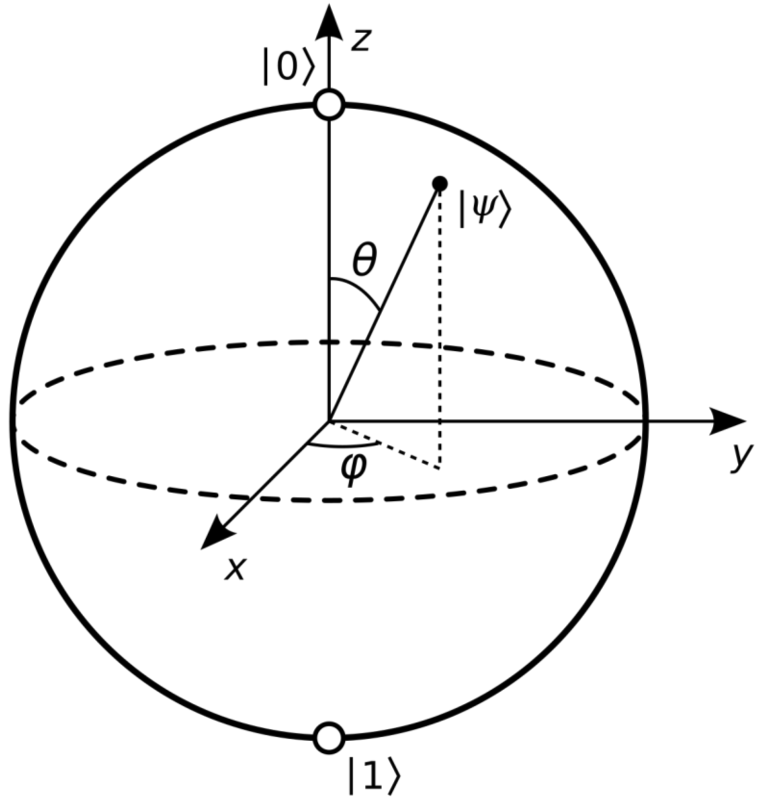
- Formally, a *Quantum Feature Map* is defined as a function that,

$$x \mapsto \rho(x)$$

$$\rho(x) = |\phi(x)\rangle\langle\phi(x)|$$



TYPES OF DATA EMBEDDING

- Basis Encoding

$$\Phi : x \mapsto |x_3 x_2 x_1\rangle \qquad x_i \in [0, 1]$$

- Angle Encoding

$$\Phi : x \mapsto U(x)|\psi_0\rangle$$

- Amplitude Encoding

$$\Phi : x \mapsto \sum_i x_i |i\rangle$$

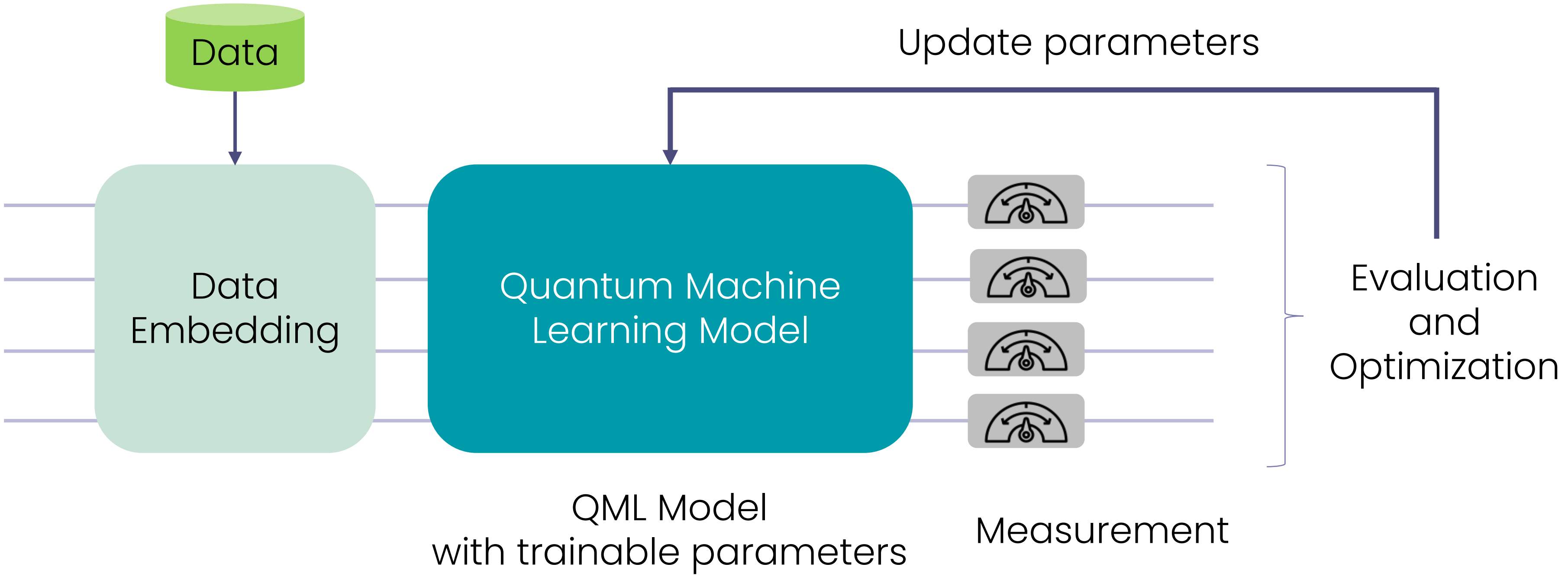
- And other feature maps

  - ZZ Feature Map $\quad U_{\phi(x)} = \exp\left(i \sum_{S \subseteq [n]} \phi_S(x) \prod_{i \in S} Z_i\right)$

TYPES OF QML ALGORITHMS

VARIATIONAL QUANTUM ALGORITHMS

Variational quantum algorithms consist of tunable unitary operations called Parameterized Quantum Circuits (PQC).



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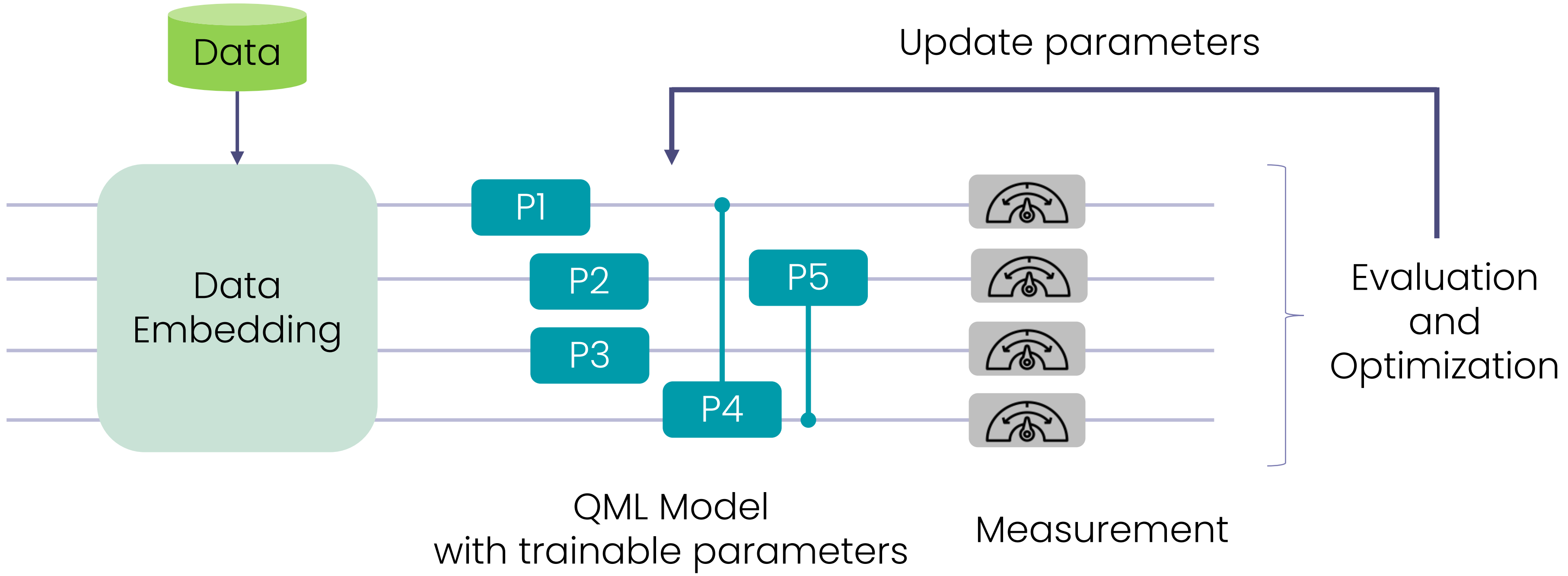
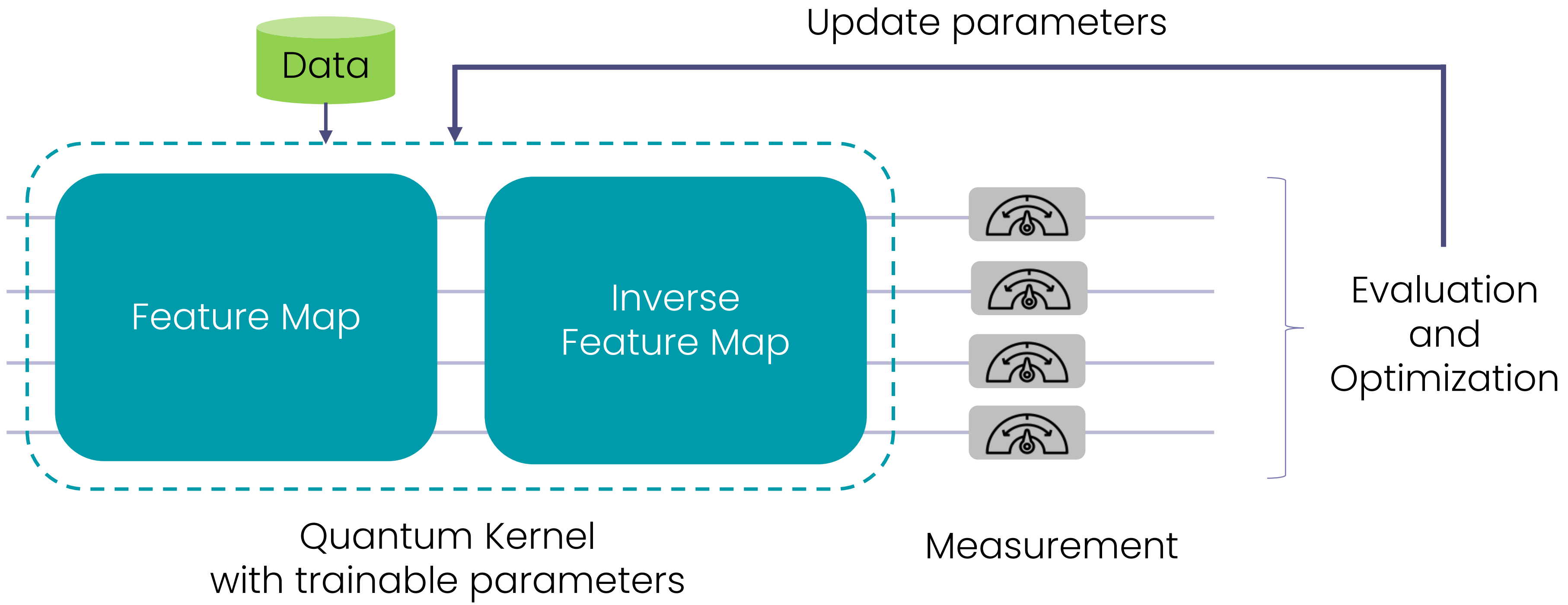


QUANTUM KERNEL METHODS

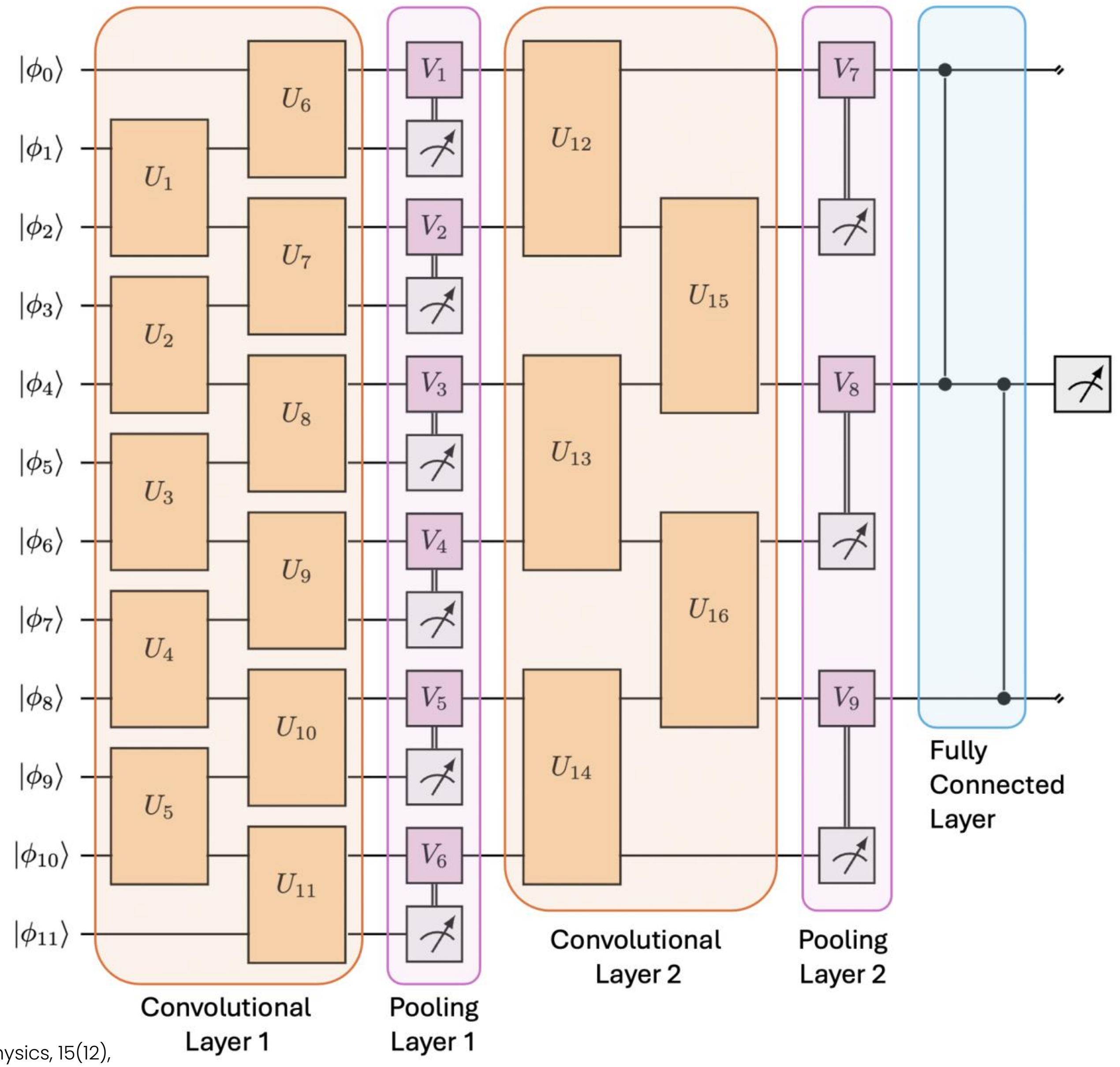
Kernel methods provide a similarity measure between data features. This similarity measure is expressed as the inner product of the data features, known as the kernel.



QUANTUM NEURAL NETWORKS

Quantum counterpart of classical neural network architecture.

For example, a quantum convolutional neural network.



Refer: Cong, I., Choi, S., & Lukin, M. D. (2019). Quantum convolutional neural networks. Nature Physics, 15(12), 1273-1278.

APPLICATIONS OF QML

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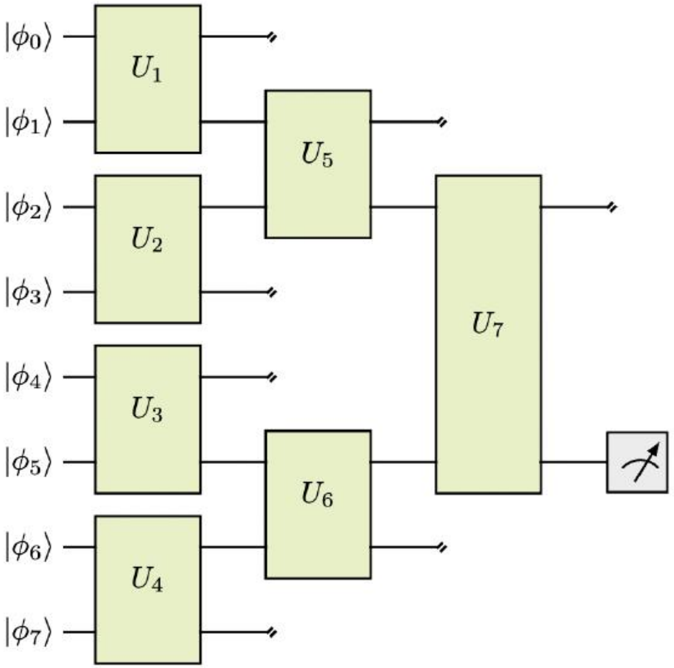
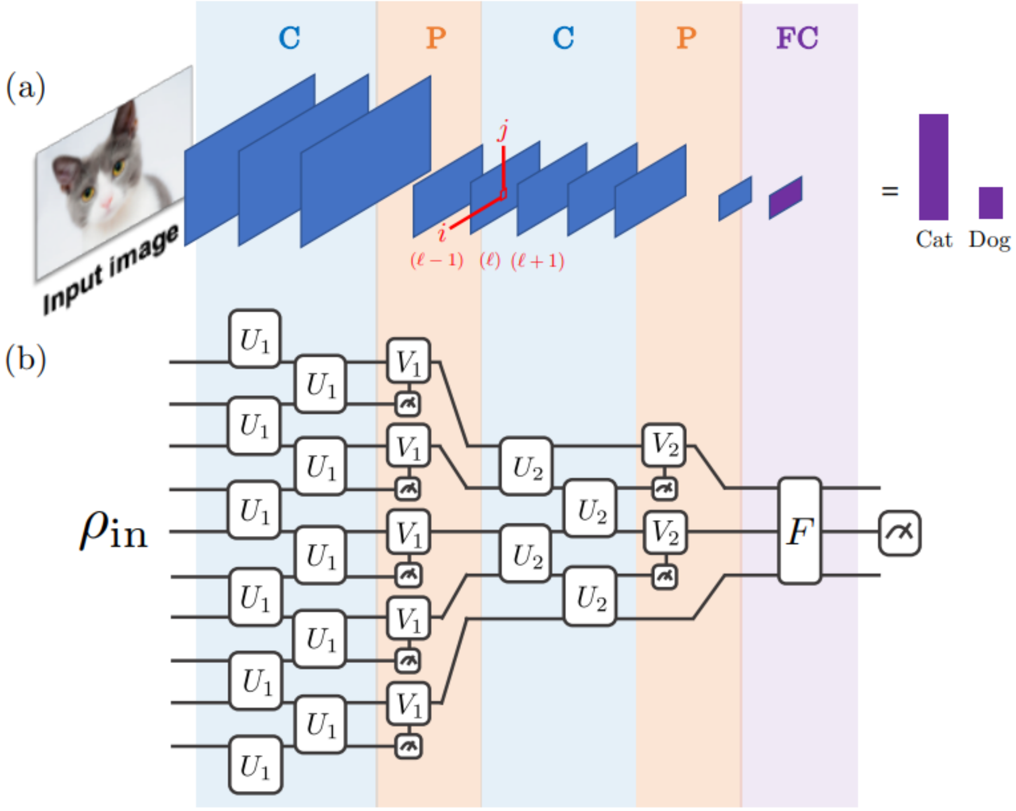
- Provide acceleration to **AI and Generative modelling**: QGANs [1], Quantum CNNs [2], Quantum Tensor Networks [3]

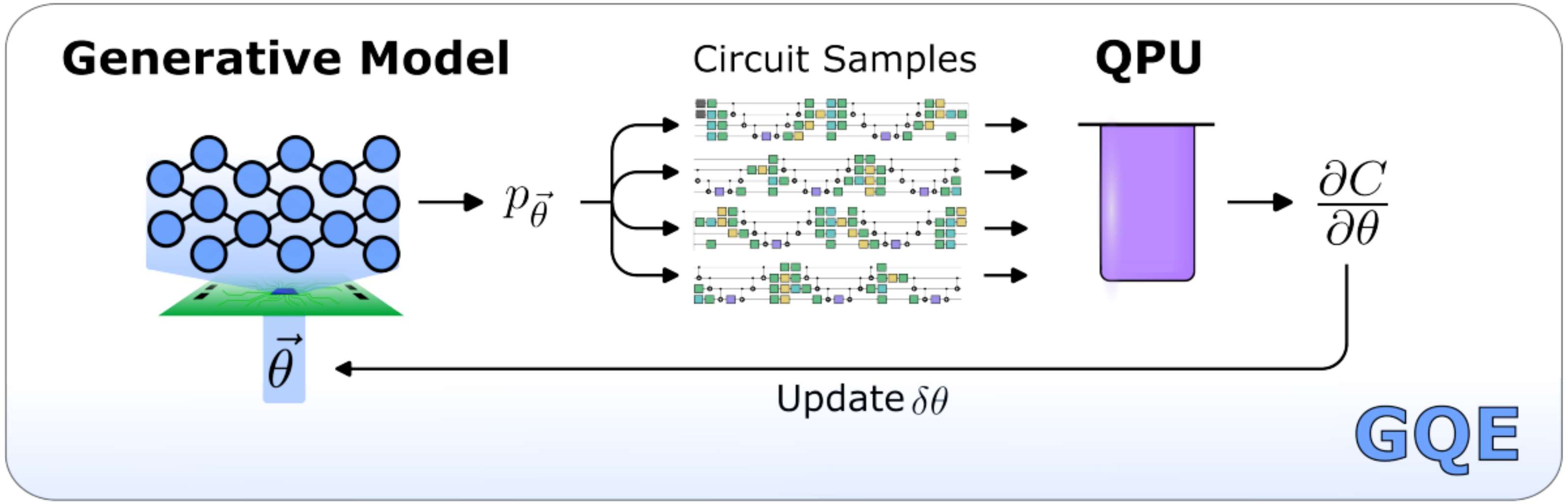




[1] Dallaire-Demers, P. L., & Killoran, N. (2018). Quantum generative adversarial networks. Physical Review A, 98(1), 012324
[2] Cong, I., Choi, S., & Lukin, M. D. (2019). Quantum convolutional neural networks. Nature Physics, 15(12), 1273-1278.
[3] Biamonte, J. (2019). Lectures on quantum tensor networks. arXiv preprint arXiv:1912.10049.

OTHER APPLICATIONS

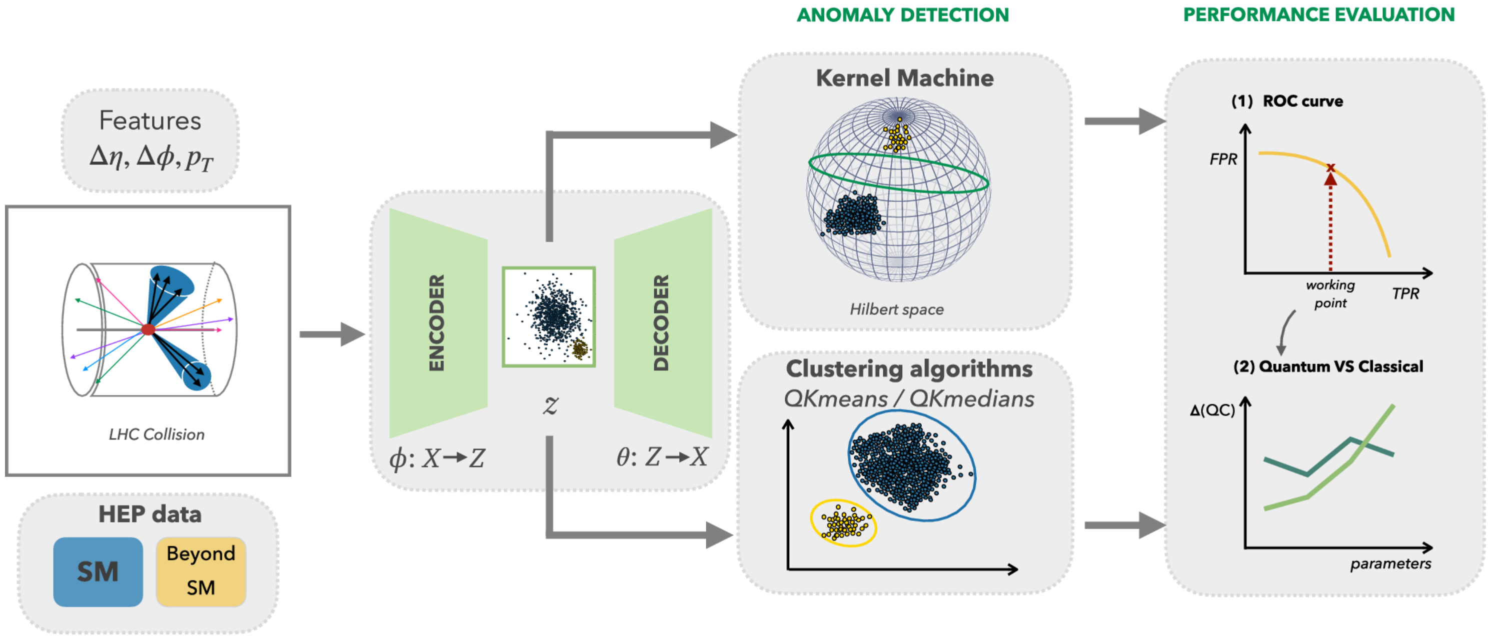
- Applications in **Chemistry and Material Science**:
  Generative Quantum Eigensolver (GQE) to find ground state energy [1],
  Quantum Boltzmann Machine [2]



[1] Nakaji, K., Kristensen, L. B., Campos-Gonzalez-Angulo, J. A., Vakili, M. G., Huang, H., Bagherimehrab, M., ... & Aspuru-Guzik, A. (2024). The generative quantum eigensolver (GQE) and its application for ground state search. arXiv preprint arXiv:2401.09253.
[2] Amin, M. H., Andriyash, E., Rolfe, J., Kulchytskyy, B., & Melko, R. (2018). Quantum boltzmann machine. Physical Review X, 8(2), 021050.

OTHER APPLICATIONS

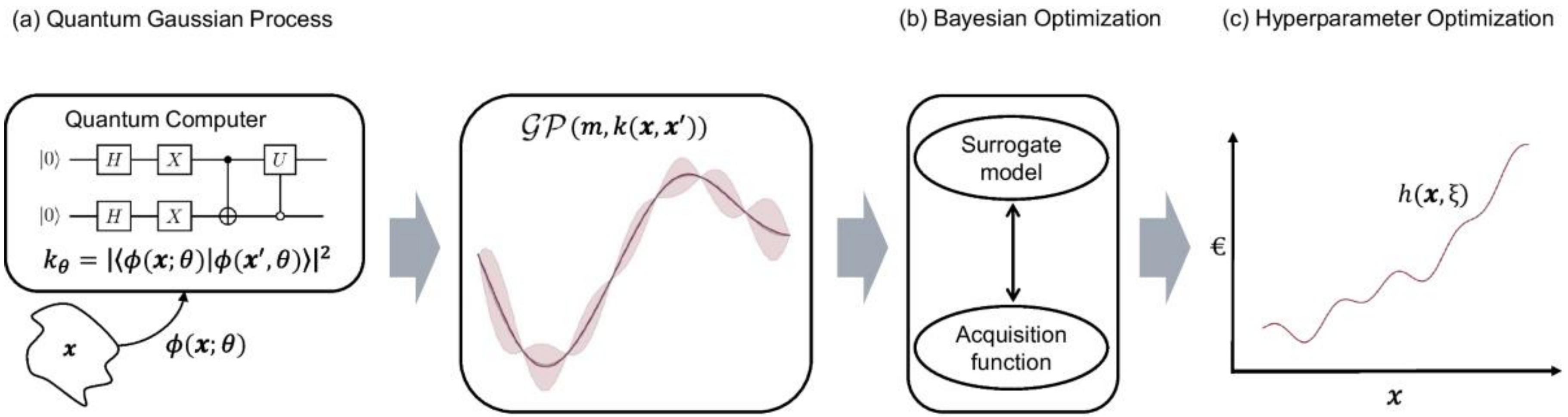
- Applications in **High-Energy Physics and Error Correction**:
  High-dimensional modeling [1], Parameter estimation, Anomaly detection [2],
  Noise modeling, Adaptive error correction



[1] Guan, W., Perdue, G., Pesah, A., Schuld, M., Terashi, K., Vallecorsa, S., & Vlimant, J. R. (2021). Quantum machine learning in high energy physics. Machine Learning: Science and Technology, 2(1), 011003.
[2] Belis, V., Woźniak, K. A., Puljak, E., Barkoutsos, P., Dissertori, G., Grossi, M., ... & Vallecorsa, S. (2024). Quantum anomaly detection in the latent space of proton collision events at the LHC. Communications Physics, 7(1), 334.

OTHER APPLICATIONS

- To solve **Optimization and Game Theory problems**:
  Combinatorial optimization,
  Financial Portfolio optimization, Risk analysis, Supply Chain optimization
  Quantum Bayesian Optimization for hyperparameter optimization [1]



[1] Rapp, F., & Roth, M. (2024). Quantum gaussian process regression for bayesian optimization. Quantum Machine Intelligence, 6(1), 5.

HANDS-ON CODING SESSION

THANK YOU

Reach out to me:
saasha.joshi@cmc.ca; saashajoshi08@gmail.com