

Universal approximation and error bounds for quantum neural networks

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joint work with Antoine Jacquier

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Quantum neural networks

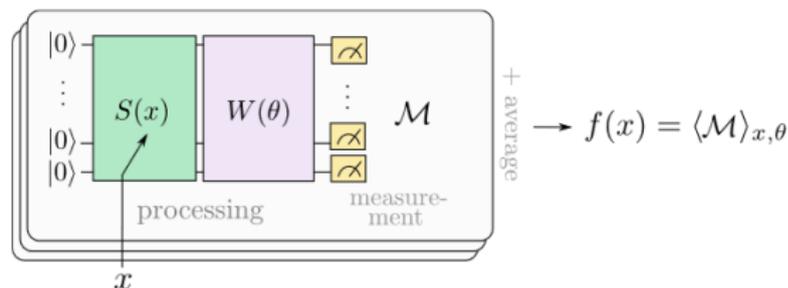


Figure: Variational quantum circuit (Schuld & Petruccione, 2021)

- Learning using quantum computers: variational quantum circuits have become a central focus of research
- Training facilitated by software (e.g. PennyLane, TensorFlow Quantum, ...)
- First universal approximation results available (A. Pérez-Salinas et al., 2020), ...
 - Approximation error? (approximation accuracy \leftrightarrow circuit size)
 - Dimensionality? Quantum advantage?

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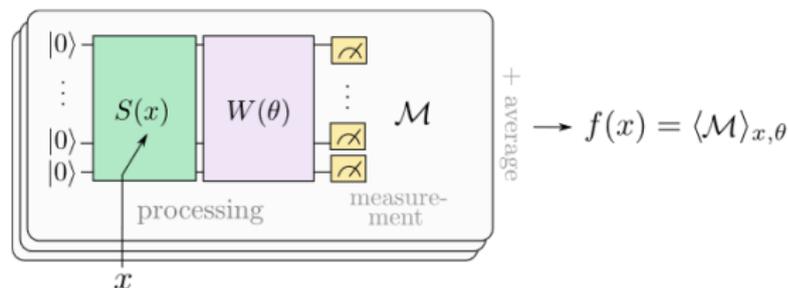


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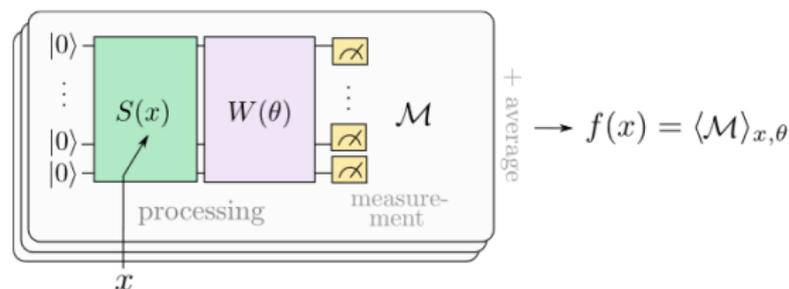


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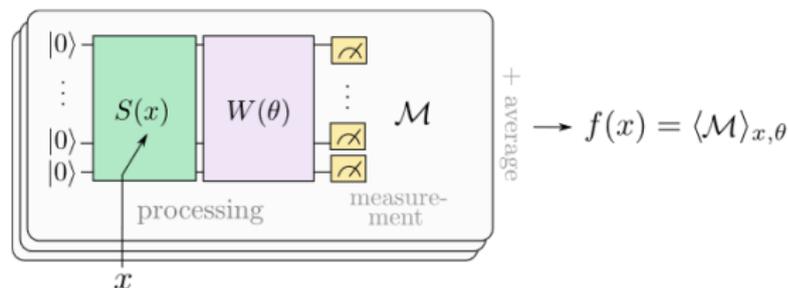


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Quantum neural network approximation bound

Fix a probability measure μ on \mathbb{R}^d to measure the error.

Theorem (G. & Jacquier (2023))

For any $n \in \mathbb{N}$ we can construct a parametrized quantum circuit operating on $\log_2(4n) + 1$ qubits with the following property: for any integrable and continuous $f: \mathbb{R}^d \rightarrow \mathbb{R}$ with $\int_{\mathbb{R}^d} |\hat{f}(\xi)| d\xi < \infty$ there exist circuit parameters θ such that the circuit output $f_{n,\theta}$ satisfies

$$\left(\int_{\mathbb{R}^d} |f(\mathbf{x}) - f_{n,\theta}(\mathbf{x})|^2 \mu(d\mathbf{x}) \right)^{1/2} \leq \frac{\int_{\mathbb{R}^d} |\hat{f}(\xi)| d\xi}{\sqrt{n}}.$$

- No curse of dimensionality occurs.
- The number of qubits is logarithmic in n .
- Analogous results for $\sup_{\mathbf{x} \in [-R,R]^d}$ -error.

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Circuit construction: Define the following gates acting on a single qubit

$$U_1^{(i)} := H R_z(-b^i) R_z(-a_d^i x_d) \cdots R_z(-a_1^i x_1) H, \quad R_z(\alpha) := \begin{pmatrix} e^{-i\frac{\alpha}{2}} & 0 \\ 0 & e^{i\frac{\alpha}{2}} \end{pmatrix}$$

$$U_2^{(i)} := \begin{pmatrix} \cos\left(\frac{\gamma^i}{2}\right) & -\sin\left(\frac{\gamma^i}{2}\right) \\ \sin\left(\frac{\gamma^i}{2}\right) & \cos\left(\frac{\gamma^i}{2}\right) \end{pmatrix}$$

with H the Hadamard gate. Now let $n_0 \in \mathbb{N}_0$ such that $\log_2(4n + n_0) \in \mathbb{N}$, write $\theta = (\mathbf{a}^{(i)}, b^{(i)}, \gamma^{(i)})_{i=1, \dots, n} \in \Theta := (\mathbb{R}^d \times \mathbb{R} \times [0, 2\pi])^n$ and define

$$\mathbf{U} := \mathbf{U}(\theta, \mathbf{x}) := \begin{bmatrix} U_1^{(1)} \otimes U_2^{(1)} & \mathbf{0}_{4 \times 4} & \mathbf{0}_{4 \times 4} & \cdots & \mathbf{0}_{4 \times 4} & \mathbf{0}_{4 \times n_0} \\ \mathbf{0}_{4 \times 4} & U_1^{(2)} \otimes U_2^{(2)} & \mathbf{0}_{4 \times 4} & \cdots & \mathbf{0}_{4 \times 4} & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \mathbf{0}_{4 \times 4} & \cdots & \mathbf{0}_{4 \times 4} & U_1^{(n-1)} \otimes U_2^{(n-1)} & \mathbf{0}_{4 \times 4} & \vdots \\ \mathbf{0}_{4 \times 4} & \cdots & \cdots & \mathbf{0}_{4 \times 4} & U_1^{(n)} \otimes U_2^{(n)} & \mathbf{0}_{4 \times n_0} \\ \mathbf{0}_{n_0 \times 4} & \cdots & \cdots & \cdots & \mathbf{0}_{n_0 \times 4} & \mathbf{1}_{n_0 \times n_0} \end{bmatrix},$$

Let $N = 4n + n_0$ and $V \in \mathbb{C}^{N \times N}$ a unitary matrix that maps $|0\rangle^{\otimes n}$ to the state $|\psi\rangle = \frac{1}{\sqrt{n}} \sum_{i=0}^{n-1} |4i\rangle$. Then we consider



Thank you!