

Full-stack Quantum Machine Learning for HEP

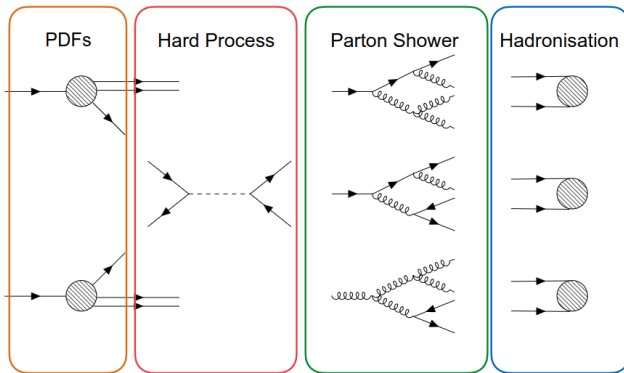
MCM23

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20 December 2023



Aim and motivation



Introductory concepts

Machine Learning helps in solving statistical problems, such as data generation, classification, regression, forecasting, etc.

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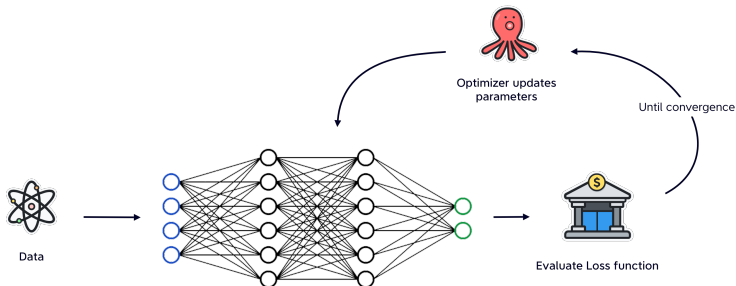
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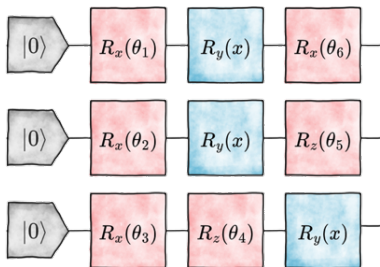
Parametric Quantum Circuits

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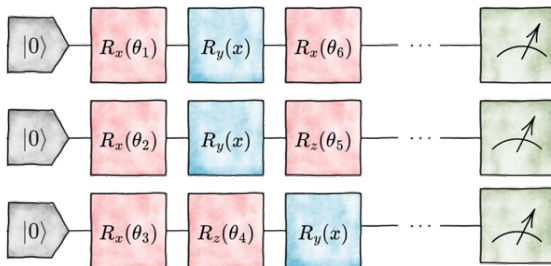
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- 👁 information is accessed calculating expected values $E[\hat{O}]$ of target observables \hat{O} on the state obtained executing \mathcal{C} .



Machine Learning

\mathcal{M} : model;

\mathcal{O} : optimizer;

\mathcal{J} : loss function.

(x, y) : data

Quantum Computation

\mathcal{Q} : qubits;

\mathcal{S} : superposition;

\mathcal{E} : entanglement.

Quantum Machine Learning - operating on qubits

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Circuit execution



Quantum Machine Learning - natural randomness

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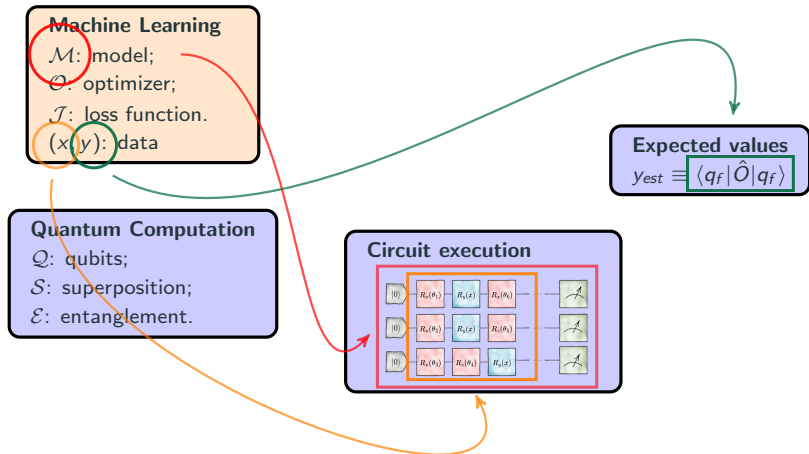
Circuit execution



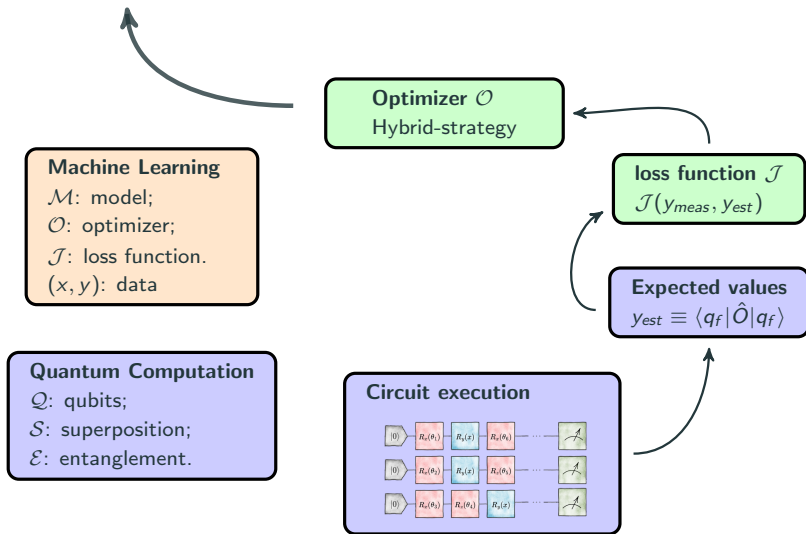
Expected values

$$y_{est} \equiv \langle q_f | \hat{O} | q_f \rangle$$

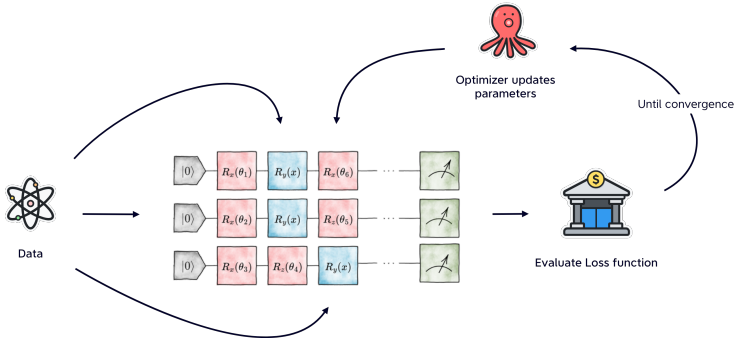
Quantum Machine Learning - encoding the problem



Quantum Machine Learning!



From ML to QML



Thank you for your attention!