Quantum Machine Learning: Opportunities and Challenges

EE350 Technical Communication

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Outline

Machine Learning

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- Helpful when the actual model is very complex and no known algorithms can discover such model or they take large amount of time or other resources.

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- Reinforcement Learning

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- Slow process. Training large data sets eates up time.

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Definition (Inner Product)

$$\langle\psi|\varphi\rangle = \begin{bmatrix} \alpha^* & \beta^* \end{bmatrix} \begin{bmatrix} \gamma \\ \delta \end{bmatrix} = \alpha^*\gamma + \beta^*\delta$$

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Postulate (State Space)

The state vector can be completely represented by a unit vector in the state space.

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Definition (Observable)

A Hermitian operator $\mathcal{O}$ which describes the projective measurement. It acts upon the state space of the system to be measured and is represented as

$$\mathcal{O} = \sum_{\lambda} \lambda P_{\lambda}$$

and P_{λ} is the *projector* with eigenvalue $\lambda \in$ eigenspace of $\mathcal{O}$.

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Postulate (**Measurement**)

A measurement on $\mathcal{O}$ will result in the eigenvalues λ with the probability of collapsing to λ is

$$p_\lambda = \| P_\lambda \langle\psi| \|^2 = \langle\psi|P_\lambda|\psi\rangle .$$

resulting in the irreversibly collapse of the state of system to

$$\frac{1}{\sqrt{p_\lambda} P_\lambda \langle\psi|}.$$

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Postulate (Evolution II)

If $\langle\psi_0|, \langle\psi_1|$ describes the state of system at times t_0, t_1 respectively then the evolution of system depends only on t_0 and t_1. It is given by

$$\langle\psi_1| = U \langle\psi_0| .$$

So far, we have studied one-qubit systems. For multi-qubit systems we introduce the following notation.

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Definition (Tensor Product (aka Kronecker Product))

For a given m, n dimensional vector spaces V, W. The tensor product of V with W (denoted by $V \otimes W$) is an mn dimensional vector spaces with elements are linear combinations of tensor products $\langle v| \otimes \langle w|$.

We can also define the tensor product of linear operators A, B over vector spaces V, W as

$$(A \otimes B)(\langle v| \otimes \langle w|) = A \langle v| \otimes B \langle w| .$$

Postulate (Composition)

For n isolated systems with states $\langle \psi_0| , \langle \psi_1| , \dots , \langle \psi_{n-1}|$, the state of the composite system is given by $\langle \psi_0| \otimes \langle \psi_1| \otimes \cdots \langle \psi_{n-1}|$

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  - Hard and out of scope problems for ML. E.g., generative models for semi-supervised and unsupervised ML
  - Datasets with quantum-like connections, turning quantum computers absolutely necessary. E.g., cognitive sciences
  - Hybrid algorithms with a difficult execution step for ML pipeline.

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- Scientists do not always know what patterns look for
- A need arises for a machine which is capable of extracting order from disorder.

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- Quantum Gibbs distributions are such alternative to MCMC

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- Real-life data sets where quantum model is simple compared with classical models must be identified.

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The Two-Stage Gambling Paradigm

[1] J. Busemeyer, Z. Wang, and R. Shiffrin, "Bayesian model comparison favors quantum over standard decision theory account of dynamic inconsistency," Decision, vol. 2, pp. 1–12, 01 2015.

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- In the first stage, people were required to gamble. If they win they get x amount of money, if they lose they lose y amount of money (both are equally likely).

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Gamble		Choice Proportions			
Win	Loss	Plan Win	Plan Loss	Final Win	Final Loss
0.8	1	0.25	0.26	0.2	0.35
0.8	0.4	0.76	0.72	0.69	0.73
2	1	0.68	0.68	0.6	0.75
2	0.4	0.84	0.86	0.76	0.89

Table: The Two-Stage Gambling Paradigm[1]

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- The person is actually in a superposition of these states

$$|\psi\rangle = \psi_{WA} |WA\rangle + \psi_{WR} |WR\rangle + \psi_{LA} |LA\rangle + \psi_{LR} |LR\rangle$$

where $|\psi_{WA}|^2$ is the probability that the person belives he won in the first stage and will accept the second stage.

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- The payoffs can be achieved using a unitary matrix which rotates ψ towards the gamble or away from it. The final state is

$$\psi_D = U\psi$$

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- Complex Dataset Representation

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- Classification can also be implemented in QAHM.

For Further Reading

- C. L. Franklin De Lima Marquezino, Renato Portugal, *A Primer on Quantum Computing*.
  SpringerBriefs in Computer Science, Springer International Publishing, 1 ed., 2019.
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