Experimenting with machine learning algorithms on quantum computers
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Abstract

A modern számítástechnika jelentős eredményei közé tartozik a gépi tanulás és mesterséges intelligancia alapvető algoritmusainak kifejlesztése és ezek hasznosságának tesztelése különböző feladatokon. Ugyanakkor az elmúlt években a kvantumszámítás is jelentős fejlődésen ment keresztül, olyannyira, hogy 2019-ben a Google kísérleti csapatának sikerült demonstrálnia a kvantumfölényt. A munka során megvizsgáljuk a két terület átfedéséből származó lehetőségeket: klasszikus adatok kvantumos feldolgozását illetve a klasszikus gépi tanulás segítségével történő kvantumos hibajavítást.

Gépi tanulási algoritmusok vizsgálata kvantumszámítógépeken
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Kivonat

A modern számítástechnika jelentős eredményei közé tartozik a gépi tanulás és mesterséges intelligancia alapvető algoritmusainak kifejlesztése és ezek hasznosságának tesztelése különböző feladatokon. Ugyanakkor az elmúlt években a kvantumszámítás is jelentős fejlődésen ment keresztül, olyannyira, hogy 2019-ben a Google kísérleti csapatának sikerült demonstrálnia a kvantumfölényt. A munka során megvizsgáljuk a két terület átfedéséből származó lehetőségeket: klasszikus adatok kvantumos feldolgozását illetve a klasszikus gépi tanulás segítségével történő kvantumos hibajavítást.

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3 Machine learning

3.1 Reinforcement learning

3.1.1 Proximal Policy optimization

$$r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} = \log \pi_{\theta}(a_t|s_t) - \log \pi_{\theta_{\text{old}}}(a_t|s_t)$$

$$\tag{1}$$

$$\delta_t = r_t + \gamma V^{\pi}(s_{t+1}) - V^{\pi}(s_t) \tag{2}$$

$$\hat{A}_t = \sum_{l=0}^{T-t-1} (\gamma \lambda)^l \delta_{t+l} = (\gamma \lambda)^0 \delta_t + (\gamma \lambda) \delta_{t+1} + \dots + (\gamma \lambda)^{T-t-1} \delta_{T-1}$$
(3)

$$L^{CLIP}(\theta) = \mathbb{E}\left[\min\left(r_t(\theta)\hat{A}_t, \operatorname{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t\right)\right] = \mathbb{E}\left[\min\left(r_t(\theta)\hat{A}_t, g(\epsilon, \hat{A}_t)\right)\right]$$
(4)

$$g(\varepsilon, \hat{A}_t) = \begin{cases} (1+\epsilon)\hat{A}_t, & \hat{A}_t \ge 0\\ (1-\epsilon)\hat{A}_t, & \text{otherwise} \end{cases}$$
 (5)

$$V_{\text{targ}}^{\pi}(s_t) = \sum_{l=0}^{T-t} \gamma^l r_{t+l} \tag{6}$$

$$L^{VF} = \mathbb{E}_{t} \left[\left(V^{\pi}(s_{t}) - V_{\text{targ}}^{\pi}(s_{t}) \right)^{2} \right]$$
 (7)

$$H[\pi] = \mathbb{E}\left[-\sum_{a \in \mathcal{A}} \pi_{\theta}(a|s_t) \log \pi_{\theta}(a|s_t)\right]$$
(8)

$$L = L^{CLIP} + c_1 L^{VF} + c_2 H[\pi]$$
 (9)

How to measure the entropy term for a quantum state ρ ? How to measure the KL-divergence of two quantum states ρ_1, ρ_2 ?

Algorithm 1 PPO-Clip

```
1: procedure PPOCLIP(\epsilon, E, N, T, K)
 2:
        for all i \in \{1, ..., E\} do
            for all n \in \{1, ..., N\} do
 3:
                Run the old policy \pi_{\text{old}} in the environment for T timesteps.
 4:
                for all t \in \{1, ..., T\} do
 5:
                    Calculate the advantage estimate \hat{A}_t
 6:
                end for
 7:
            end for
 8:
            for all k \in \{1, ..., K\} do
 9:
                Sample a batch of size M \leq NT and optimize the surrogate loss L.
10:
            end for
11:
12:
        end for
13: end procedure
```

4 Quantum Machine Learning

4.1 Parametric quantum circuits

4.2 Calculating the gradients of the parameters

A Mathematical preliminaries

A.1 Hilbert spaces

Definition 1. Hilbert-space

Given a field T (real or complex), a vector space \mathcal{H} endowed with an inner product, is called a Hilbert-space, if it is a complete metric space with respect to the distance function induced by the inner product. The inner product is a map $\langle \cdot | \cdot \rangle : \mathcal{H} \times \mathcal{H} \to T$, for which $\forall x, y, z \in \mathcal{H}$:

- $\bullet \langle x|x\rangle > 0$
- $\langle x|x\rangle = 0 \iff x = \mathbf{0} \in \mathcal{H}$
- $\langle x|y\rangle = \langle y|x\rangle^*$, where * denotes complex conjugation.
- $\langle x | \alpha y + \beta z \rangle = \alpha \langle x | y \rangle + \beta \langle x | z \rangle$, where $\alpha, \beta \in T$

The norm induced by this inner product is a map $||\cdot||: \mathcal{H} \to T$ defined as

$$||x|| = \sqrt{\langle x|x\rangle},$$

And the metric induced by this norm is defined as

$$d(x,y) = ||x - y|| = \sqrt{\langle x - y|x - y\rangle}.$$

The space \mathcal{H} is said to be complete if every Cauchy-sequence is convergent with respect to the norm, and the limit is in \mathcal{H} . That is, each sequence $x_1, x_2, ...$, for which

$$\forall \varepsilon > 0 \ \exists N(\varepsilon) \ so, \ that \ n > m > N(\varepsilon) \implies ||x_n - x_m|| < \varepsilon.$$

Definition 2. Linear functional

Let \mathcal{H} be a Hilbert-space over the field T. Then, the map $\varphi: \mathcal{H} \to T$ is called a linear functional, if

$$\varphi(\alpha x + \beta y) = \alpha \varphi(x) + \beta \varphi(y), \ \forall \alpha, \beta \in T, x, y \in \mathcal{H}.$$

Definition 3. Dual space

Given a Hilbert-space \mathcal{H} , its dual space, \mathcal{H}^* is the space of all continuous linear functionals from the space \mathcal{H} into the base field. The norm of an element in \mathcal{H}^* is

$$||\varphi||_{\mathcal{H}^*} \stackrel{def}{=} \sup_{||x||=1, x \in \mathcal{H}} |\varphi(x)|.$$

Theorem 1. Riesz representation theorem

For every element $y \in \mathcal{H}$, there exists a unique element $\varphi_y \in \mathcal{H}^*$, defined by

$$\varphi_y(x) = \langle y|x\rangle, \ \forall x \in \mathcal{H}.$$

The mapping $y \mapsto \varphi_y$ is an antilinear mapping i.e. $\alpha y_1 + \beta y_2 \mapsto \alpha^* \varphi_{y_1} + \beta^* \varphi_{y_2}$, and the Riesz-representation theorem states that this mapping is an antilinear isomorphism. The inner product in \mathcal{H}^* satisfies

$$\langle \varphi_x | \varphi_y \rangle = \langle x | y \rangle^* = \langle y | x \rangle.$$

Moreover, $||y||_{\mathcal{H}} = ||\varphi_y||_{\mathcal{H}^*}$.

Definition 4. Dirac-notation

From now on, the elements in \mathcal{H} will be denoted by $|x\rangle$ and their corresponding element in \mathcal{H}^* as $\langle x|$.

A.2 Linear operators on Hilbert spaces

Definition 5. Linear operators

A map $\tilde{A}: \mathcal{H}_1 \to \mathcal{H}_2$ is a linear operator, if

$$\hat{A}(\alpha | x\rangle + \beta | y\rangle) = \alpha(\hat{A} | x\rangle) + \beta(\hat{A} | y\rangle).$$

Remark 1. If not stated otherwise, we will assume that $\mathcal{H}_1 = \mathcal{H}_2 = \mathcal{H}$.

Remark 2. Operators will be denoted with a hat $(\hat{\cdot})$.

Definition 6. Bounded linear operators

A linear operator $\hat{A}: \mathcal{H} \to \mathcal{H}$ is bounded, if

$$\exists m \in \mathbb{R} : |\langle v | \hat{A} | v \rangle| \le m \langle v | v \rangle, \, \forall \, |v \rangle \in \mathcal{H}$$

Remark 3. The set of all bounded operators on \mathcal{H} is denoted $\mathcal{B}(\mathcal{H})$.

Definition 7. Commutators and anticommutators

Since operators usually do not commute, its useful to define their commutator and anticommutator:

$$[\hat{A}, \hat{B}] = \hat{A}\hat{B} - \hat{B}\hat{A}$$
$$\{\hat{A}, \hat{B}\} = \hat{A}\hat{B} + \hat{B}\hat{A}$$

Definition 8. Operator norm

The operator norm of an operator \hat{A} is defined as

$$||\hat{A}|| \stackrel{def}{=} \inf\{c \ge 0 : ||\hat{A}|v\rangle|| \le c|||v\rangle||, \,\forall |v\rangle \in \mathcal{H}\}$$

Definition 9. Trace-class operators

An operator \hat{A} is called trace-class if it admits a well defined and finite trace $\operatorname{Tr}\left[\hat{A}\right] = \sum_{i} \langle j|\hat{A}|j\rangle$

Definition 10. Positive operators

An operator \hat{A} is called positive if $\langle v|\hat{A}|v\rangle \geq 0$, $\forall |v\rangle \in \mathcal{H}$. If $\hat{A} = \sum_{j} \lambda_{j} |j\rangle \langle j|$ then \hat{A} is positive if $\lambda_{j} \geq 0$.

Definition 11. Projections An operator $\Pi: \mathcal{H} \to \mathcal{H}$ is a projection if $\Pi^2 = \Pi$.

A.3 Hermitian Operators, Unitary Operators, Spectral theorem, Hadamard-lemma

Definition 12. Hermitian adjoint

Consider a **bounded** linear operator $\hat{A}: \mathcal{H} \to \mathcal{H}$. The hermitian adjoint of \hat{A} is a bounded linear operator $\hat{A}^{\dagger}: \mathcal{H} \to \mathcal{H}$ which satisfies

$$\langle y|\,\hat{A}\,|x\rangle = \left(\langle x|\,\hat{A}^{\dagger}\,|y\rangle\right)^*,\,\,\forall\,|x\rangle\,,|y\rangle\in\mathcal{H}.$$
 (10)

Definition 13. Hermitian operators

A bounded linear operator $\hat{H}: \mathcal{H} \to \mathcal{H}$ is Hermitian if

$$\hat{H} = \hat{H}^{\dagger}, i.e. \ \hat{H} |x\rangle = \hat{H}^{\dagger} |x\rangle, \ \forall |x\rangle \in \mathcal{H}.$$
 (11)

Definition 14. Unitary operator

A bounded linear operator $\hat{U}: \mathcal{H} \to \mathcal{H}$ is unitary if

$$\hat{U}\hat{U}^{\dagger} = \hat{U}^{\dagger}\hat{U} = 1, \text{ in other words, } \hat{U}^{\dagger} = \hat{U}^{-1}. \tag{12}$$

Definition 15. Eigenvalues and eigenvectors

Consider bounded linear operator \hat{A} . If exist a vectors $|k\rangle \in \mathcal{H}$ such that

$$\hat{A}|k\rangle = \lambda_k |k\rangle \,, \tag{13}$$

then $|k\rangle$ is called an eigenvector of \hat{A} and λk is the corresponding eigenvalue.

An important property of Hermitian operators is that they can be diagonalized with real eigenvalues. This is formally stated by the spectral theorem:

Theorem 2. The Spectral theorem

Let \hat{A} be a bounded Hermitian operator on some Hilbert-space \mathcal{H} . Then there exists an orthonormal basis in \mathcal{H} which consists of the eigenvectors of \hat{A} and each eigenvalue of \hat{A} is real.

This means that any bounded Hermitian operator \hat{H} can be decomposed as

$$\hat{H} = \sum_{k} \lambda_k \hat{P}_k = \sum_{k} \lambda_k |k\rangle\langle k| \tag{14}$$

where λ_k and $|k\rangle$ are the eigenvalues and eigenvectors of \hat{H} .

Definition 16. Exponential of operators If X is a linear operator, we can define the exponential of X:

$$e^X = \sum_{n=0}^{\infty} \frac{X^n}{n!}$$

Important: The product of exponentials of operators generally isn't equal to the exponential of their sum:

$$e^X e^Y = e^{Z(X,Y)} \neq e^{X+Y},$$

where Z(X,Y) is given by the Baker-Campbell-Hausdorff formula:

$$Z(X,Y) = X + Y + \frac{1}{2}[X,Y] + \frac{1}{12}[X,[X,Y]] - \frac{1}{12}[Y,[X,Y]] - \frac{1}{24}[Y,[X,[X,Y]]] - \frac{1}{720}([[[X,Y],Y],Y],Y] + [[[Y,X],X],X],X]) + \dots$$

It is however equal if [X, Y] = 0:

if
$$[X, Y] = 0 \implies e^X e^Y = e^{X+Y}$$

There are 2 important special cases:

Theorem 3. The Hadamard-lemma

$$e^{X}Ye^{-X} = Y + [X, Y] + \frac{1}{2!}[X, [X, Y]] + \frac{1}{3!}[X, [X, [X, Y]]] + \dots$$

Theorem 4. If X and Y commute with their commutator, i.e. [X, [X, Y]] = [Y, [X, Y]] = 0, then:

$$e^X e^Y = e^{X+Y+\frac{1}{2}[X,Y]}$$

Theorem 5. If [X,Y] = sY with $s \in \mathbb{C}, s \neq 2i\pi n, n \in \mathbb{Z}$ then:

$$e^X e^Y = \exp\left(X + \frac{s}{1 - e^{-s}}Y\right)$$

A.4 Pure and mixed quantum states

Definition 17. Quantum states

A quantum state of a quantum system is a mathematical entity that provides a probability distribution for the outcomes of each possible measurement on the system.

Definition 18. Pure quantum states

Pure quantum states are quantum states that can be described by a vector $|\psi\rangle$ of norm 1.

If one multiplies a pure quantum state by a complex scalar $e^{i\alpha}$, then the new state is physically equivalent to the former, thus $|\psi\rangle$ and $e^{i\alpha}|\psi\rangle$ are the same pure state. The transformation $|\psi\rangle \to e^{i\alpha}|\psi\rangle$ does not change the outcomes of measurements on the state, however the phase α is important in quantum algorithms.

Example. For example, the states $\frac{1}{\sqrt{2}}(|0\rangle + e^{i\pi}|1\rangle)$ and $\frac{1}{\sqrt{2}}(|0\rangle + e^{i\frac{\pi}{2}}|1\rangle)$ are not the same quantum state, but in both states there is 50-50 percent probability of measuring $|0\rangle$ and $|1\rangle$.

Definition 19. Density Matrix

A quantum state $\hat{\rho}$ is a trace-1, self-adjoint, positive semidefinite operator. The set of quantum states is

$$\mathcal{S}(\mathcal{H}) = \{\hat{\rho} : \hat{\rho} \ge 0, \hat{\rho} = \hat{\rho}^{\dagger}, \operatorname{Tr}[\hat{\rho}] = 1\}$$

A quantum state is pure if and only if $\hat{\rho}^2 = \hat{\rho}$. Also, if ρ is a pure state, then it can be written as $\hat{\rho} = |\psi\rangle\langle\psi|$. The operator ρ is called the density operator or density matrix.