

Sampling Probability Distributions à la Grover

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In this blog post, I will describe Grover's sampling algorithm, an algorithm given in Ref.[1], for sampling probability distributions using a quantum computer. I will also compare very briefly Grover's sampling algorithm with the sampling algorithm used by my computer program Quibbs.

I will use my customary notation. Recall that I like to use $Bool = \{0, 1\}$, $P_0 = |0\rangle\langle 0|$, $P_1 = |1\rangle\langle 1|$. Also $N_S = 2^{N_B}$ is the number of states for N_B bits. Qubit positions will be labeled by Greek letters.

Consider N_B qubits labeled $\vec{\alpha} = (\alpha_{N_B-1}, \dots, \alpha_1, \alpha_0)$ and a single auxilliary qubit labeled β . Suppose $|\Psi\rangle$ is a state of the $N_B + 1$ qubits $(\vec{\alpha}, \beta)$ and let $P_0(\beta) = |0\rangle_\beta\langle 0|_\beta$. Define an operator G by

$$G = -(-1)^{|\Psi\rangle\langle\Psi|}(-1)^{P_0(\beta)}. \quad (1)$$

Grover's sampling algorithm involves calculating $G^M|\Psi\rangle$ for some suitable integer M . Note that if we define a unit vector $|\Psi_0\rangle$ by

$$|\Psi_0\rangle = \frac{P_0(\beta)|\Psi\rangle}{\sqrt{\langle\Psi|P_0(\beta)|\Psi\rangle}}, \quad (2)$$

then

$$P_0(\beta)|\Psi\rangle = (|\Psi_0\rangle\langle\Psi_0|)|\Psi\rangle, \quad (3)$$

and

$$P_0(\beta)|\Psi_0\rangle = (|\Psi_0\rangle\langle\Psi_0|)|\Psi_0\rangle. \quad (4)$$

Hence, $P_0(\beta)$ equals $|\Psi_0\rangle\langle\Psi_0|$ when acting on space $span(|\Psi\rangle, |\Psi_0\rangle)$. If we define

$$\tilde{G} = -(-1)^{|\Psi\rangle\langle\Psi|}(-1)^{|\Psi_0\rangle\langle\Psi_0|}, \quad (5)$$

then

$$G^M |\Psi\rangle = \tilde{G}^M |\Psi\rangle . \quad (6)$$

We see that Grover's sampling algorithm uses the original Grover's "search" algorithm with a starting state $|s'\rangle = |\Psi\rangle$ and a target state $|t\rangle = |\Psi_0\rangle$.

Grover's sampling algorithm uses for $|\Psi\rangle$ the state

$$|\Psi\rangle = \frac{1}{\sqrt{N_S}} \sum_{\vec{x} \in \text{Bool}^{N_B}} \left(\sqrt{Pr(\vec{x})} |0\rangle_\beta + \sqrt{1 - Pr(\vec{x})} |1\rangle_\beta \right) |\vec{x}\rangle_{\vec{\alpha}} , \quad (7)$$

where $Pr()$ is the probability distribution that we wish to sample. For this $|\Psi\rangle$, one gets

$$|\Psi_0\rangle = \sum_{\vec{x} \in \text{Bool}^{N_B}} \sqrt{Pr(\vec{x})} |0\rangle_\beta |\vec{x}\rangle_{\vec{\alpha}} . \quad (8)$$

To build the state $|\Psi\rangle$ of Eq.7, one can proceed as follows. Define operators U and Γ by

$$U = \Gamma(\beta, \vec{\alpha}) H^{\otimes N_B}(\vec{\alpha}) , \quad (9)$$

$$\Gamma(\beta, \vec{\alpha}) = \exp \left\{ -i\sigma_Y(\beta) \sum_{\vec{x} \in \text{Bool}^{N_B}} \arccos(\sqrt{Pr(\vec{x})}) P_{\vec{x}}(\vec{\alpha}) \right\} \quad (10a)$$

$$= \sum_{\vec{x} \in \text{Bool}^{N_B}} \exp \left\{ -i\sigma_Y(\beta) \arccos(\sqrt{Pr(\vec{x})}) \right\} P_{\vec{x}}(\vec{\alpha}) \quad (10b)$$

It follows that

$$U |0^{N_B}\rangle_{\vec{\alpha}} |0\rangle_\beta = \quad (11a)$$

$$= \frac{1}{\sqrt{N_S}} \sum_{\vec{x} \in \text{Bool}^{N_B}} \exp \left\{ -i\sigma_Y(\beta) \arccos(\sqrt{Pr(\vec{x})}) \right\} |\vec{x}\rangle_{\vec{\alpha}} |0\rangle_\beta \quad (11b)$$

$$= |\Psi\rangle . \quad (11c)$$

Thus,

$$|\Psi\rangle = U |0^{N_B+1}\rangle , \quad (12)$$

and

$$(-1)^{|\Psi\rangle\langle\Psi|} = U (-1)^{|0^{N_B+1}\rangle\langle 0^{N_B+1}|} U^\dagger \quad (13)$$

The operator Γ is what I like to call a $U(2)$ multiplexor with N_B controls. It can be expanded into multiply controlled NOTS and single-qubit rotations using the computer program “Multiplexor Expander”, described in Ref.[2].

Some drawbacks of Grover’s sampling algorithm are as follows:

- Grover’s sampling algorithm uses the full probability distribution $Pr(x)$ whereas Quibbs uses only conditional probabilities of $Pr(x)$. All the classical MCMC (Markov Chain Monte Carlo) methods also use only conditional probabilities.
- In general, for arbitrary $Pr()$, the operator Γ cannot be compiled, either exactly or to a good approximation, with polynomial efficiency (i.e., it cannot be decomposed into a SEO (Sequence of Elementary Operations) whose length scales polynomially in N_B).

References

- [1] Lov Grover, “Rapid Sampling Through Quantum Computing” ariv:quant-ph/9912001,
- [2] R.R. Tucci, “Code Generator for Quantum Simulated Annealing” by R.R. Tucci, arXiv:0908.1633