Typicality Algorithm for Partial Trace Estimation

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Background Introduction

Introduction

- Study of quantum systems has gained significant attention due to its potential applications in quantum computing, quantum communication, and quantum sensing
- These systems are described by density matrices, which provide a comprehensive description of the quantum state of a system
- When we have a composite quantum system described by a density matrix, we often want to study the properties of one of its subsystems without considering the rest

What is Partial Trace?

Introduction Oo

Partial trace is a mathematical operation used to obtain the reduced density matrix from the density matrix of a larger composite system.

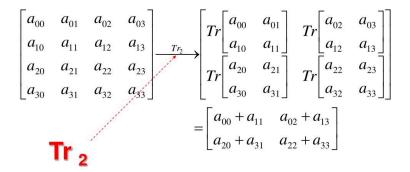


Figure 1: Partial Trace Example

Computation and Storage Cost

- ▶ If we have an explicit representation of a matrix *A*, computing the partial trace of *A* is simple.
- ▶ What if *A* is a complicated matrix function?

$$Eg: A = exp(-H/t)$$

- ▶ When the size of H is $2^{20} * 2^{20}$ or even greater, the cost to compute and/or store A is too expensive.
- ► Hence a cheaper, faster algorithm is required.

A Stochastic Partial Trace Estimator

Essential of setting up:

$$\operatorname{tr}(M) = \mathbb{E}[\mathbf{v}^T M \mathbf{v}], \qquad \operatorname{tr}^m(M) \approx \frac{1}{m} \sum_{i=1}^m \mathbf{v}^T M \mathbf{v}$$

where v is a random vector with independent and identically distributed entries having a standard normal distribution.

Extend this property to partial trace:

$$\begin{bmatrix} \operatorname{tr}(A_{1,1}) & \operatorname{tr}(A_{1,2}) & \cdots & \operatorname{tr}(A_{1,a}) \\ \operatorname{tr}(A_{2,1}) & \operatorname{tr}(A_{2,2}) & \cdots & \operatorname{tr}(A_{2,a}) \\ \vdots & \vdots & \ddots & \vdots \\ \operatorname{tr}(A_{a,1}) & \operatorname{tr}(A_{a,2}) & \cdots & \operatorname{tr}(A_{a,a}) \end{bmatrix} = \mathsf{E} \begin{bmatrix} \mathbf{v}^T A_{1,1} \mathbf{v} & \mathbf{v}^T A_{1,2} \mathbf{v} & \cdots & \mathbf{v}^T A_{1,a} \mathbf{v} \\ \mathbf{v}^T A_{2,1} \mathbf{v} & \mathbf{v}^T A_{2,2} \mathbf{v} & \cdots & \mathbf{v}^T A_{2,a} \mathbf{v} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{v}^T A_{a,1} \mathbf{v} & \mathbf{v}^T A_{a,2} \mathbf{v} & \cdots & \mathbf{v}^T A_{a,a} \mathbf{v} \end{bmatrix}$$

However, introducing randomness will definitely lead to a potentially large variance of the estimator.

A Variance Reduce Algorithm

► Notice the following property of partial trace:

$$\operatorname{tr}_b(A) = \operatorname{tr}_b(\widetilde{A}) + \operatorname{tr}_b(A - \widetilde{A}).$$

We can compute the trace of \widetilde{A} explicitly, and use the stochastic partial trace estimator we developed earlier to estimate $\operatorname{tr}_b(A-\widetilde{A})$, ie:

$$\operatorname{tr}_b(\mathbf{A}) \approx \operatorname{tr}_b(\widetilde{A}) + \operatorname{tr}_b^m(A - \widetilde{A}).$$

- $ightharpoonup \widetilde{A}$ should be chosen so that $\operatorname{tr}_b^m(A-\widetilde{A})$ produces a relatively smaller variance.
- ▶ Generalize A = exp(-H/t) to any arbitrary matrix function A = f(H) using Krylov Subspace Method, which uses matrix polynomial functions to approximate A.

Numerical Experiments

$$\rho^*(\beta) := \frac{tr_b(exp(-\beta H))}{tr(tr_b(exp(-\beta H)))}, \beta = \frac{1}{t}$$
$$\tilde{A} := QQ^T A Q Q^T, Q \in \mathbb{R}^{d_A * k}$$

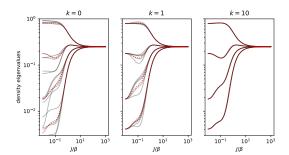
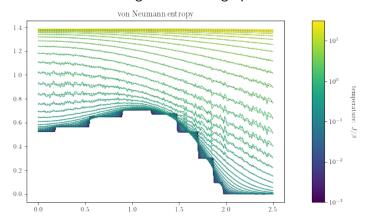


Figure 2: comparison of k = 0, k = 1, and k = 10

Adaptive Point Estimation

► Our blackbox function generates the graph below:



► To estimate the points at which the function changes, use binary search method with sample points.

Supercomputer

- ➤ To study the performance of different quantum systems, we will conduct numerical experiments on the NYU Greene Supercomputer.
- ► The problem is well-suited for parallel computing:
- ► Inputs are independent of each other without the need to exchange information.

Q & A

Any Questions?