# Classical simulation of quantum circuits

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# The power of quantum computation



What makes quantum circuits/processes so hard to simulate?

- Exponentially large Hilbert space?
- Superposition of many 'classical' processes?
- Entanglement?

# **Stabilizers and Gottesman-Knill**

An efficiently simulatable subtheory

- A class of quantum circuits that can be efficiently simulated:
  - Initialize in a stabilizer state includes entangled states (Bell, GHZ, cluster)
  - Unitaries in the Clifford group including Paulis, CNOT, Hadamard, Phase gate
  - Measure in basis of stabilizer states

Aaronson and Gottesman, PRA (2004)

- Computation is somehow "classical"
- Stabilizer circuits can be viewed as supervening on a classical dynamical computation through the use of a nonnegative quasiprobability representation

# Quasiprobability representations



### **Quasiprobabilities**

Quasiprobability representations: another way of describing quantum mech.

–  $\,$  Classical hidden variables on a phase space  $\Lambda$ 

 $ho o W_
ho(\lambda)$  Like a probability distribution $U o W_U(\lambda|\lambda')$  Like a conditional probability $E o W(E|\lambda)$  Like a conditional probability

- Measurements  $E \to W(E|\lambda)$
- Real valued, normalized like probability distributions
- Born rule as you'd expect:  $\operatorname{Tr}[EU\rho U^{\dagger}] = \sum_{\lambda,\lambda'\in\Lambda} W(E|\lambda)W_U(\lambda|\lambda')W_{\rho}(\lambda')$
- But can go negative!

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States

Unitaries

## **Quasiprobabilities**

Quasiprobability representations: another way of describing quantum mech.

- Classical hidden variables on a phase space

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## **Quasiprobabilities**

Quasiprobability representations: another way of describing quantum mech.



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# **Negativity and nonclassicality**





Classical

Quantum

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## Quasiprobabilities for finite quantum systems

Finite-dimensional quantum systems typically use a discrete phase space



Gibbons, Hoffman, Wootters, PRA (2004); Gross, JMP (2006)

# **Negativity and nonclassicality**





## Classical

Quantum

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# **Operationalizing nonclassicality**

#### Negativity in a quasiprobability can be related to notions of nonclassicality

- Nonnegativity = simulatability

#### Monte Carlo on the hidden variables

Veitch, Ferrie, Gross, Emerson, NJP (2012) Mari and Eisert, PRL (2012)

Negativity = contextuality

Negativity in all quasiprobability representations is equivalent to a proof of contextuality

Spekkens, PRL (2007)

- Negativity = magic

Negative states are those that can be distilled to magic states, that can supplement Clifford gates to allow universal quantum computation

> Veitch, Mousavian, Gottesman, Emerson, NJP (2014) Howard, Wallman, Veitch, Emerson, Nature (2014)



# Structure of our result

> Can we push the boundary on simulatability?

- 1. Quantify negativity review
- 2. Poly-precision estimators for Born rule probabilities
- 3. Born rule probabilities as quasiprobabilistic sum over trajectories
- 4. Construct a true probability distribution of trajectories as a Markov chain
- 5. Construct an unbiased estimator
- 6. Bound convergence of this estimator in terms of the amount of negativity

#### **Main Result**

Estimator converges to true quantum mechanical probability at a rate determined by the amount of negativity in the circuit

If the negativity is polynomially bounded -> efficiently yields a poly-precision estimate

Pashayan, Wallman, Bartlett (2015)

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# Quantifying negativity





### Quantifying negativity

Veitch, Mousavian, Gottesman, Emerson, NJP (2014)

Define the *negativity* of a state: the 1-norm of its quasiprobability representation

$$\mathcal{M}_{\rho} = \sum_{\lambda \in \Lambda} |W_{\rho}(\lambda)|$$

Negativity is multiplicitive, not additive (could take the log of this quantity)

If  $W_{
ho}$  is nonnegative, then  $\mathcal{M}_{
ho}=1$ 



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## Negativity for states, unitaries, measurements



# Estimating measurement probabilities



# Trajectories in phase space

What do quasiprobabilities tell us about the probabilities of measurement outcomes?



Can we estimate p by sampling from some true probability distribution?

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## What's a good estimator?

What would make a good estimator of a probability associated with a measurement outcome?



Poly-precision estimator: for any fixed confidence, yields an estimate within  $\varepsilon$  of the true Born rule probability using resources that scale polynomially in  $1/\varepsilon$ .

## True probabilities from quasiprobabilities

Quasiprobability for a trajectory  $W(\vec{\lambda}) = W(E|\lambda_L)W_{U_L}(\lambda_L|\lambda_{L-1})\cdots W_{U_1}(\lambda_1|\lambda_0)W_{\rho}(\lambda_0)$ May be negative, so how do we sample?

First attempt: sample from 
$$\Pr(\vec{\lambda}) = \frac{|W(\vec{\lambda})|}{\mathcal{M}_c}$$
  $\mathcal{M}_c = \sum_{\vec{\lambda}} |W(\vec{\lambda})|$ 

Estimate of the probability for each trajectory is  $\hat{q}_1 = \mathcal{M}_c \text{Sign}[W(\vec{\lambda})]$ 

This gives an unbiased estimator, minimizes the range, and has the smallest variance of all estimators over the space of trajectories...

But is impossible to sample from!

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## **Our algorithm**

Circuit with an efficient description (product input + output, local unitaries)

1. Sample initial point in trajectory from modified distribution

 $\Pr(\lambda_0) = |W_{\rho}(\lambda_0)| / \mathcal{M}_{\rho}$ 

2. At each timestep l=0,...,L, sample from conditional distribution

 $\Pr(\lambda_l|\lambda_{l-1}) = |W_{U_l}(\lambda_l|\lambda_{l-1})| / \mathcal{M}_{U_l}(\lambda_{l-1})|$ 

3. Estimate based on single trajectory

$$\hat{p}_1(\lambda) = \mathcal{M}_{\rho} \operatorname{Sign}[W_{\rho}(\lambda_0)] \prod_{l=1}^{L} \left[ \mathcal{M}_{U_l}(\lambda_{l-1}) \operatorname{Sign}[W_{U_l}(\lambda_l | \lambda_{l-1})] \right] W_E(\lambda_L)$$

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## **Properties of this estimate**

Properties of estimator  $\hat{p}_1(\lambda) = \mathcal{M}_{\rho} \operatorname{Sign}[W_{\rho}(\lambda_0)] \prod_{l=1}^{L} \left[ \mathcal{M}_{U_l}(\lambda_{l-1}) \operatorname{Sign}[W_{U_l}(\lambda_l | \lambda_{l-1})] \right] W_E(\lambda_L)$ 

- Efficiently computable
- Unbiased estimator of Born rule probability

$$\begin{split} \langle \hat{p}_{1}(\vec{\lambda}) \rangle &= \sum_{\vec{\lambda}} \hat{p}_{1}(\vec{\lambda}) \operatorname{Pr}(\vec{\lambda}) \\ &= \sum_{\vec{\lambda}} \hat{p}_{1}(\lambda) \frac{|W_{\rho}(\lambda_{0})|}{\mathcal{M}_{\rho}} \prod_{l=1}^{L} \frac{|W_{U_{l}}(\lambda_{l}|\lambda_{l-1})|}{\mathcal{M}_{U_{l}}(\lambda_{l-1})} \\ &= \sum_{\vec{\lambda}} W_{\rho}(\lambda_{0}) \prod_{l=1}^{L} W_{U_{l}}(\lambda_{l}|\lambda_{l-1}) W_{E}(\lambda_{L}) \\ &= \operatorname{Pr}(E|\rho, U) \end{split}$$

Total negativity bound:
$$\mathcal{M} = \mathcal{M}_{
ho} \prod_{l=1}^{L} \mathcal{M}_{U_l} \max_{\lambda_L} |W_E(\lambda_L)|$$

– Not a probability! Lies in the interval  $\left[-\mathcal{M},+\mathcal{M}\right]$ 

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# Sampling and convergence

Compute  $\hat{p}_1(\lambda)$  for *s* independent trajectories, take the average

- Unbiased, and bound to the interval  $[-\mathcal{M},+\mathcal{M}]$
- Use Hoeffding inequality for upper bound on convergence:

Average of s samples will be within  $\epsilon$  of the quantum probability with probability  $1-\delta$  if the total number of samples taken is

$$s(\epsilon, \delta) = \frac{2}{\epsilon^2} \mathcal{M}^2 \ln(2/\delta)$$

If the total negativity grows at most polynomially in N, we have an efficient estimate of the quantum probability to within  $\epsilon=1/poly(N)$ , with an exponentially small failure probability

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## **Example**

- Random 100-qutrit Clifford circuit
- Initialize with k magic states

$$\frac{1}{\sqrt{3}}(|0\rangle + \xi|1\rangle + \xi^8|2\rangle)$$
$$\xi = \exp(2\pi i/9)$$

- Measure "0" on the first qutrit
- Number of samples chosen using

$$s(k) = \frac{2}{\epsilon^2} c^{2k} \ln(2/\delta)$$



- Target precision  $\epsilon$ =0.01 with 95% confidence

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# **Examples of quasiprobabilities**

- Odd-d qudit discrete Wigner function
  - All stabilizer states and measurements (+ some more) are nonnegative

Gibbons, Hoffman, Wootters, PRA (2004); Gross, JMP (2006)

- Real-valued qubit discrete Wigner function
  - Real stabilizer states and CSS-preserving unitaries

Delfosse, Guerin, Bian, Raussendorf, PRX (2015) See also Bravyi, Smith, and Smolin, arXiv:1506.01396

- Qubit quasiprobabilities with nonnegative bases
  - 1, 2, 3, or 4 nonnegative bases and finite subgroups of SU(2) no entanglement
     Wallman and Bartlett, PRA (2012)
- Continuous-variable Wigner function
  - Coherent states and squeezed states, linear optics and squeezing
  - Implications for BosonSampling?
- Dual frames can be overcomplete additional flexibility

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## **Conclusions and future directions**

- Operational meaning of negativity: a measure that bounds the efficiency of a classical estimation of probabilities
- Efficient estimation vs sparcity



- Conditioning on intermediate measurements?
  - Naïve inclusion: calculating conditional probabilities requires exponential precision
  - Or make the conditional operation coherent, and delay measurement to the end: can add negativity
- From estimation to simulation
- An ontology for quantum computing?

