The Power of Quantum Fourier Sampling

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Classical Complexity Theory

• P

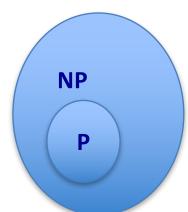
Class of problems efficiently solved on classical computer

NP

- Class of problems with efficiently checkable solutions
- Characterized by SAT
 - Input: $\Psi:\{0,1\}^n \to \{0,1\}$
 - n-variable boolean formula

» E.g.,
$$(x_1 \lor x_2 \lor x_3) \land (x_1 \lor -x_2 \lor x_6) \land \dots$$

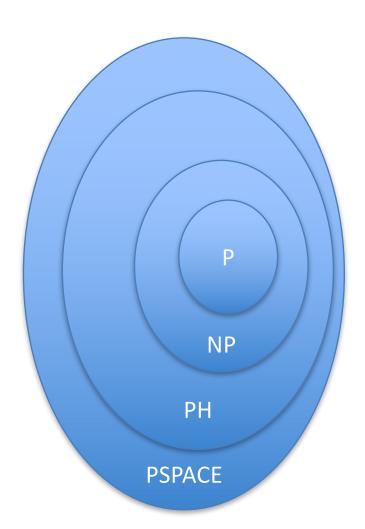
- Problem: $\exists x_1, x_2, ..., x_n$ so that $\Psi(x)=1$?
- SAT is NP-complete



Beyond NP

Tautology

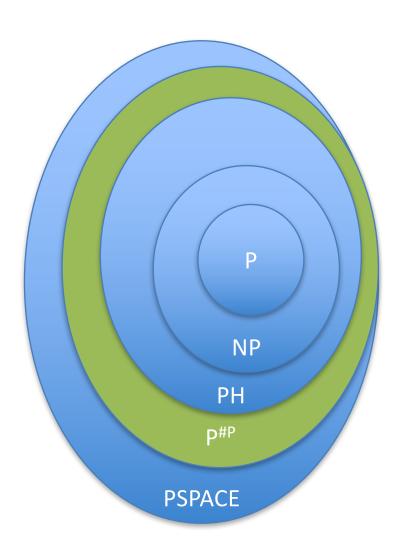
- •Input: $\Psi:\{0,1\}^n \to \{0,1\}$
- $\forall x \Psi(x)=1$?
- Complete for coNP
- Don't believe that coNP=NP
- •Generalize **SAT** and **Tautology** by adding quantifiers:
 - •QSAT₂ is the version of the SAT problem with 2 quantifiers
 - •E.g., $\exists x_1x_2x_3...x_{n/2} \forall x_{n/2+1}x_{n/2+2},...,x_n$ so that $\Psi(x)=1$?
 - •Consider problems QSAT₃,QSAT₄,QSAT₅...QSAT_n
 - •Conjectured to get strictly harder with increasing number of quantifiers (or else there's a *collapse*!)
- Σ_k is class of problems solvable with a $QSAT_k$ box
- PH is class of problems solvable with a QSAT_{O(1)} box
- PSPACE is class of problems solvable with a QSAT_n box



Complexity of Counting

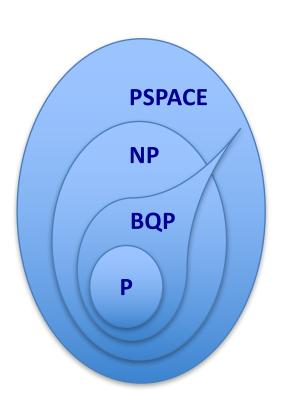
#SAT

- Input: Ψ: $\{0,1\}^n \rightarrow \{0,1\}$
- Problem: How many satisfying assignments to Ψ?
- #SAT is complete for #P
- PH⊆P^{#P} [Toda'91]
- Permanent $[X] = \sum_{\sigma \in S_n} \prod_{i=1} X_{i,\sigma(i)}$ is **#P-hard**



How powerful are quantum computers?

- BQP: The class of decision problems solvable by quantum computers in polynomial time
- Certainly P⊆BQP
- But why should BQP\(\psi\)P (or NP or PH)?
 - Shor's algorithm: Factoring ∈ BQP
 - But little reason to believe Factoring is not in
 - In fact, if Factoring is NP-hard then PH collapses
 - Oracle separations, see [e.g., Aaronson'10, F., Umans'11]
 - In short, not much is known!



Separations from sampling problems

- Starting with [DT'02][BJS'10] we know that there are distributions that can be sampled quantumly that cannot be sampled exactly classically (unless PH collapse)
 - Quantumly: Efficiently prepare a quantum state on n qubits and measure in standard basis
 - Distribution is over measurement outcomes
 - Classically: No efficient classical randomized algorithm can sample from exactly the same distribution
- Our focus: "Approximate sampling" hardness result
 - Want a hardness result even if the classical sampler samples from distribution 1/poly(n) close in total variation distance from quantum distribution
 - Why are we interested in this?
 - "To model experimental error"
 - Other complexity separations would follow (i.e., fBQP⊄fBPP [Aaronson'10])

Construction of quantumly sampleable distribution **D**_{PER}

- Goal: efficiently prepare a quantum state in which each amplitude is proportional to the **Permanent** of a different matrix
- Sketch of procedure:
 - 1. Prepare the "permutation matrix state"
 - Quantum state on n² qubits uniformly supported only on those n! permutation matrices
 - 2. Apply a quantum Fourier transform $H^{\bigotimes n^2}$
 - i.e., apply Hadamard on each of n² qubits
 - 3. Measure in standard basis to sample
 - Claim: Each amplitude is proportional to the Permanent of a different {±1}^{n x n} matrix

What's happening?

- Recall, Permanent(x₁,x₂,...,x_{n^2}) is a multilinear polynomial of degree n
- Our quantum sampling algorithm (omitting normalization):

All possible multilinear monomials over n^2 variables $M_1,...M_{2^{n}}$ $M_1(X_1),M_2(X_1),...,M_{2^{n}}$ $M_2(X_1),...,M_{2^{n}}$ $M_2(X_1),...,M_{2^{n}}$ $M_1(X_1),M_2(X_1),...,M_{2^{n}}$ $M_2(X_1),...,M_{2^{n}}$ $M_2(X_1),...,M_{2^{n}}$ $M_1(X_2,X_1),...,M_2(X_1),...,M_2(X_1)$ $M_1(X_2,X_1),...,M_2(X_1),...,M_2(X_1)$ $M_2(X_1,X_2)$ $M_2(X_1,X_2$

This is supported on the monomials in the **Permanent**

Classical hardness sketch

- Recall: D_{PER} is a distribution over all $\{\pm 1\}^{n \times n}$ matrices X with probabilities proportional to $Permanent^2[X]$
- Assume there's a classical algorithm that samples from distribution close in total variation distance to \mathbf{D}_{PER}
- Key tool: Stockmeyer's algorithm
 - Input: Classical sampler and an outcome
 - Output: A $(1\pm\epsilon)$ -multiplicative estimate to the probability of this outcome in time $poly(n,1/\epsilon)$ with an **NP** oracle
 - i.e., for $\varepsilon=1/\text{poly}(n)$, this is in $BPP^{NP}\subseteq\Sigma_3$
- Our strategy: Chose a random $\{\pm 1\}^{n \times n}$ matrix X and use Stockmeyer's algorithm to estimate outcome probability of X \approx Permanent²[X]
 - Since our sampler is approximate, can't trust it on any single outcome probability
 - Markov inequality: Most of the probabilities must be close to the true probabilities
 - So we end with a BPP^{NP} algorithm for estimating the Permanent² of most matrices
- Is estimation task #P-hard? If so then $P^{\#P} \subseteq BPP^{NP} \subseteq \Sigma_3$
 - But we know that $PH \subseteq P^{\#P}$ by Toda's theorem
 - So PH⊆ Σ_3 (Collapse!)

How hard is "Approximating" the Permanent?

- Our result: If there is an approximate sampler for D_{PER} then there's a PH algorithm that "computes Permanent" with two caveats:
 - Only "works" with high probability (over choice of matrix)
 - 2. "Works" means obtains a multiplicative estimate
- We can show that either of these weaknesses alone would be #P-hard!
- Don't know how to prove #P-hardness for both of these weakness!
 - This is exactly the same reason other two "approximate" sampling results need conjectures [Aaronson and Arkhipov, Bremner, Montanaro and Shepherd]...

Generalizing the argument

- Unlike the results of [Aaronson & Arkhipov '12] and [Bremner, Montanaro & Shepherd '16] we can generalize our argument to rely on alternative hardness conjectures
 - Can generalize the **Permanent** to any "efficiently specifiable polynomial"
 - Can generalize the entries of the matrices and the distribution over matrices (e.g., iid Gaussian instead of random sign matrix)
- If any of these conjectures are true, we show the desired "approximate sampling" separation

Thanks!