

The Power of Quantum Fourier Sampling

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Based on [arxiv:1507.05592](https://arxiv.org/abs/1507.05592)

I. Complexity Theory Basics

Classical Complexity Theory

- **P**

- Class of problems efficiently solved on classical computer

- **NP**

- Class of problems with efficiently checkable solutions

- Characterized by **SAT**

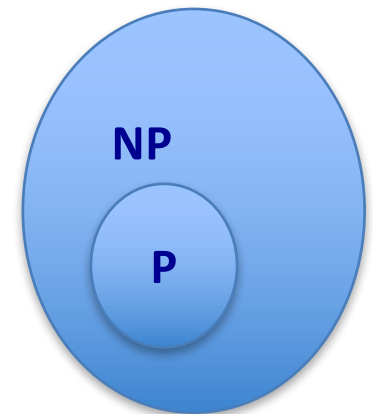
- Input: $\Psi: \{0,1\}^n \rightarrow \{0,1\}$

- n-variable 3-CNF formula

- » E.g., $(x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_6) \wedge \dots$

- Problem: $\exists x_1, x_2, \dots, x_n$ so that $\Psi(x)=1$?

- Could use a box solving **SAT** to solve any problem in **NP**



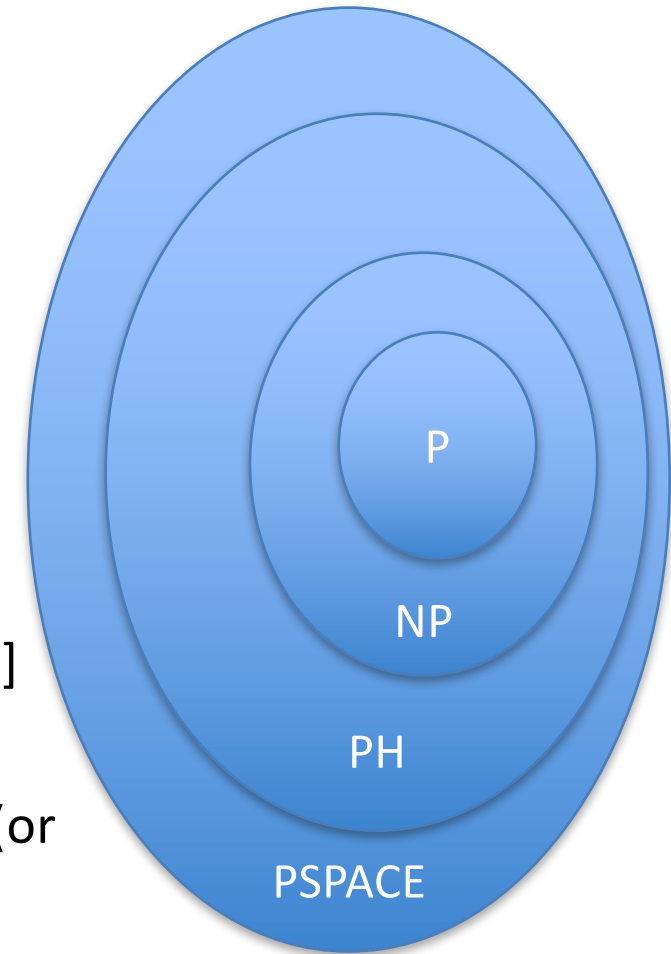
Beyond NP

- **Tautology**

- Input: $\Psi: \{0,1\}^n \rightarrow \{0,1\}$
- $\forall x \Psi(x)=1?$
- Complete for **coNP**

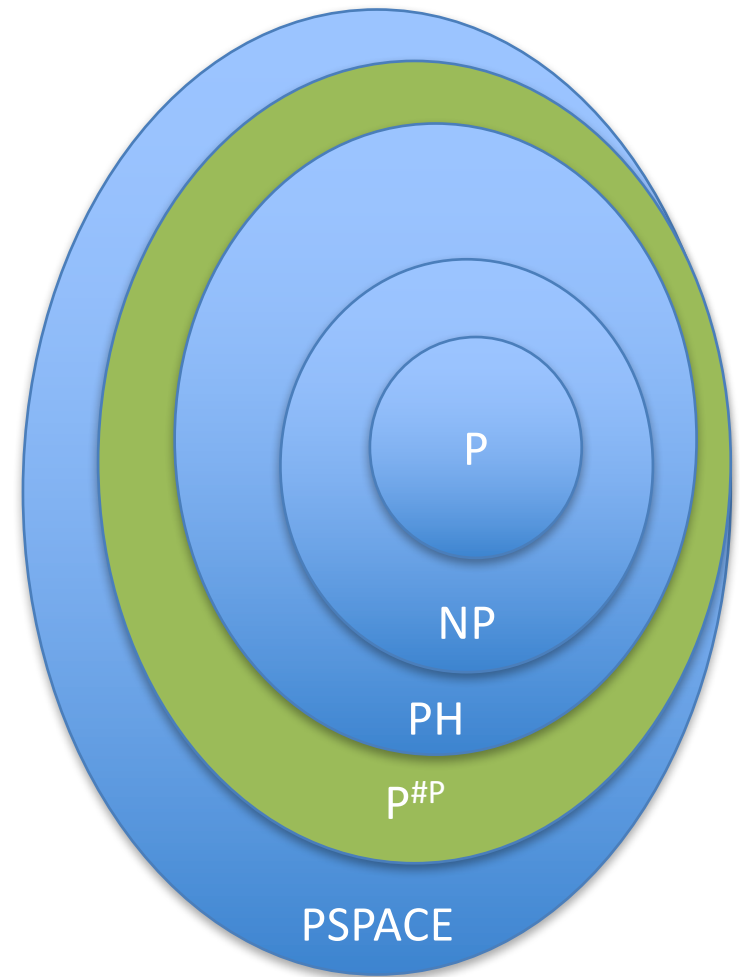
- **QSAT_k**

- Generalizes **SAT** and **Tautology**
- Input: $\Psi: \{0,1\}^n \rightarrow \{0,1\}$ & partitioning $S_1, S_2, \dots, S_k \subseteq [n]$
 - Problem: $\exists x_{S_1} \forall x_{S_2}, \dots, \forall x_{S_k} \Psi(x)=1?$
 - Thought to be strictly harder with larger k's (or else there is 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: $\Psi:\{0,1\}^n \rightarrow \{0,1\}$
 - Problem: How many satisfying assignments to Ψ ?
- **#SAT** is complete for **#P**
- **PH** \subseteq **P#P** [Toda'91]
- $\text{Permanent}[X] = \sum_{\sigma \in S_n} \prod_{i=1}^n X_{i,\sigma(i)}$ is **#P**-hard



Complexity of *Approximate* Counting

- Given efficiently computable $f:\{0,1\}^n \rightarrow \{0,1\}$ and $y \in \{0,1\}$
 - Want to compute $\Pr_{x \sim U}[f(x)=y]$ exactly
 - This is **#P**-hard
 - Because $\Pr_x[f(x)=1] = \{\# \text{ } x\text{'s so that } f(x)=1\} / 2^n = \sum_x f(x) / 2^n$
 - This is as hard as counting number of satisfying assignments to formula Ψ
- However, *estimating* $\Pr_{x \sim U}[f(x)=y]$ to within multiplicative error can be done in **Σ_3** , the third level of **PH** [Stockmeyer '83]

- So for input $f:\{0,1\}^n \rightarrow \{0,1\}$ and $\epsilon > 0$ can output α :

$$(1 - \epsilon) \sum_x f(x) \leq \alpha \leq (1 + \epsilon) \sum_x f(x)$$

in time $\text{poly}(n, 1/\epsilon)$ with **Σ_3** oracle

- But, situation is very different for $g:\{0,1\}^n \rightarrow \{+1,-1\}$
 - Computing $\sum_x g(x)$ exactly is still **#P**-hard
 - Estimating $\sum_x g(x)$ to within $(1 \pm \epsilon)$ *multiplicative* error is **#P**-hard!
 - Binary search & Padding
 - Can generalize this hardness:
 - Estimating $(\sum_x g(x))^2$ to within $(1 \pm \epsilon)$ *multiplicative* error is **#P**-hard
 - Why is this so much harder than the $\{0,1\}$ -valued case?
 - Cancellations

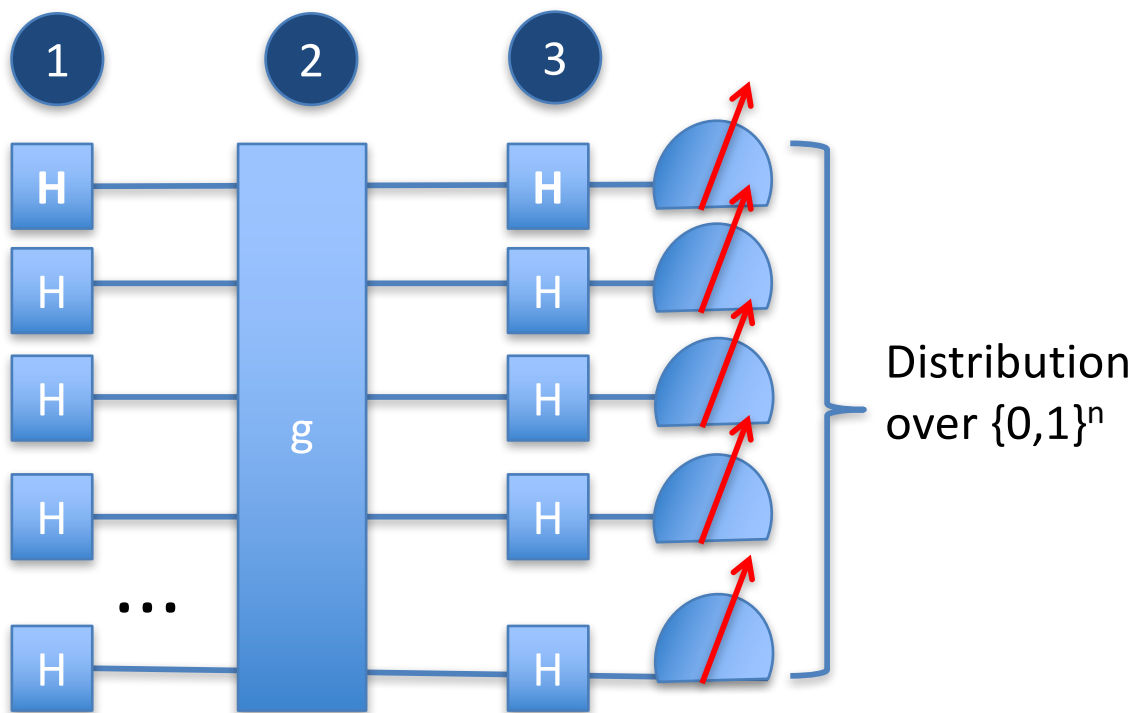
Today

- Want to show that quantum computers are capable of sampling from distributions that cannot be sampled by randomized classical algorithms
- Two constructions of hard distributions
 1. “Exact” construction
 - No classical algorithm can sample from exactly the same distribution as the quantum algorithm
 2. “Approximate” construction
 - *Goal:* Show no classical algorithm can sample from any distribution even close (in total variation distance) to quantum distribution
 - Why do we want to do this?
 - “To model error”
 - [Aaronson ‘11] has shown that such a result would imply a “function problem” complexity separation (i.e., $\mathbf{FBQP} \not\subseteq \mathbf{FBPP}$)...
- *Upshot:* We’ll reach many of the same conclusions of the *BosonSampling* [AA’10] proposal with a (conceptually) much simpler setup. Our proposal also weakens the hardness conjectures needed by [AA’10], but as of yet does not resolve them....

II. “Exact” Construction [implicit in *Aaronson ‘11*]

Quantumly sampleable distribution

- *Recall:* For efficiently computable function $g:\{0,1\}^n \rightarrow \{\pm 1\}$, giving a $(1 \pm \varepsilon)$ mult error estimate to $(\sum_x g(x))^2$ is **#P**-hard
- Consider the following quantum circuit:



$$\begin{array}{ll}
 \frac{1}{\sqrt{2^n}} \sum_{x \in \{0,1\}^n} |x\rangle & \text{1} \\
 \frac{1}{\sqrt{2^n}} \sum_{x \in \{0,1\}^n} g(x) |x\rangle & \text{2} \\
 \frac{1}{2^n} \sum_{y \in \{0,1\}^n} \sum_{x \in \{0,1\}^n} -1^{\langle x,y \rangle} g(x) |y\rangle & \text{3}
 \end{array}$$

Key point: The probability of seeing $00\dots 0$ is $(\sum_x g(x))^2 / 2^{2n}$

Exact classical sampler collapses **PH**

- Suppose C is a randomized algorithm that samples the outcome distribution so by definition:

$$\Pr_{r \sim U_{p(n)}} [C(r) = y] = \frac{1}{2^{2n}} \left(\sum_{x \in \{0,1\}^n} -1^{\langle x, y \rangle} g(x) \right)^2$$

- Note that $\mathbf{p} = \Pr_r[C(r) = 00\dots 0] = (\sum_x g(x))^2 / 2^{2n}$ encodes a **#P**-hard quantity
- Use Stockmeyer's algorithm to find a $(1 \pm \epsilon)$ multiplicative error estimate to \mathbf{p}
- Puts **P^{#P}** \subseteq **Σ_3** (but Toda tells us that **PH** \subseteq **P^{#P}**)
- **PH** \subseteq **Σ_3** (collapse!!)

How *robust* is this prior construction?

- Not very!!
 - Hardness based on a single exp. small probability
 - *Definition:* For distribution X over $\{0,1\}^n$:

Given as input $\epsilon > 0$, suppose a classical randomized algorithm samples from any distribution Y , with $|X - Y|_1 < \epsilon$, in time $\text{poly}(n, 1/\epsilon)$

Call such a classical algorithm an “*Approximate Sampler*” for X

- **Our goal:** Find a quantumly sampleable X , where the existence of a classical “Approximate Sampler” would cause **PH** collapse.
- Prior construction doesn’t work! (Adversary just “erases” probability we care about)

III. “Approximate” Construction using Quantum Fourier Sampling [F., Umans ‘15]

Construction of distribution D_{PER}

- Define an efficiently computable function $h:[n!] \rightarrow \{0,1\}^{n^2}$
 - Takes a permutation in S_n to its trivial encoding as an $n \times n$ permutation matrix
 - Can be computed efficiently using e.g., Lehmer codes
 - Note h is 1-to-1 and h^{-1} also efficiently computable
- Quantum sampler:
 - Two steps:
 - Prepare uniform superposition over $n \times n$ permutation matrices
 - Prepare uniform superposition over S_n
 - Apply h , followed by h^{-1}
 - Hit with Hadamard on each of n^2 qubits
- Measure in standard basis

$$\frac{1}{\sqrt{n!}} \sum_{\sigma \in S_n} |\sigma\rangle |00\dots 0\rangle \quad 1$$

$$\frac{1}{\sqrt{n!}} \sum_{\sigma \in S_n} |\sigma\rangle |h(\sigma)\rangle$$

$$\frac{1}{\sqrt{n!}} \sum_{\sigma \in S_n} |\sigma \oplus h^{-1}(h(\sigma))\rangle |h(\sigma)\rangle$$

$$\frac{1}{\sqrt{n!}} \sum_{\sigma \in S_n} |h(\sigma)\rangle$$

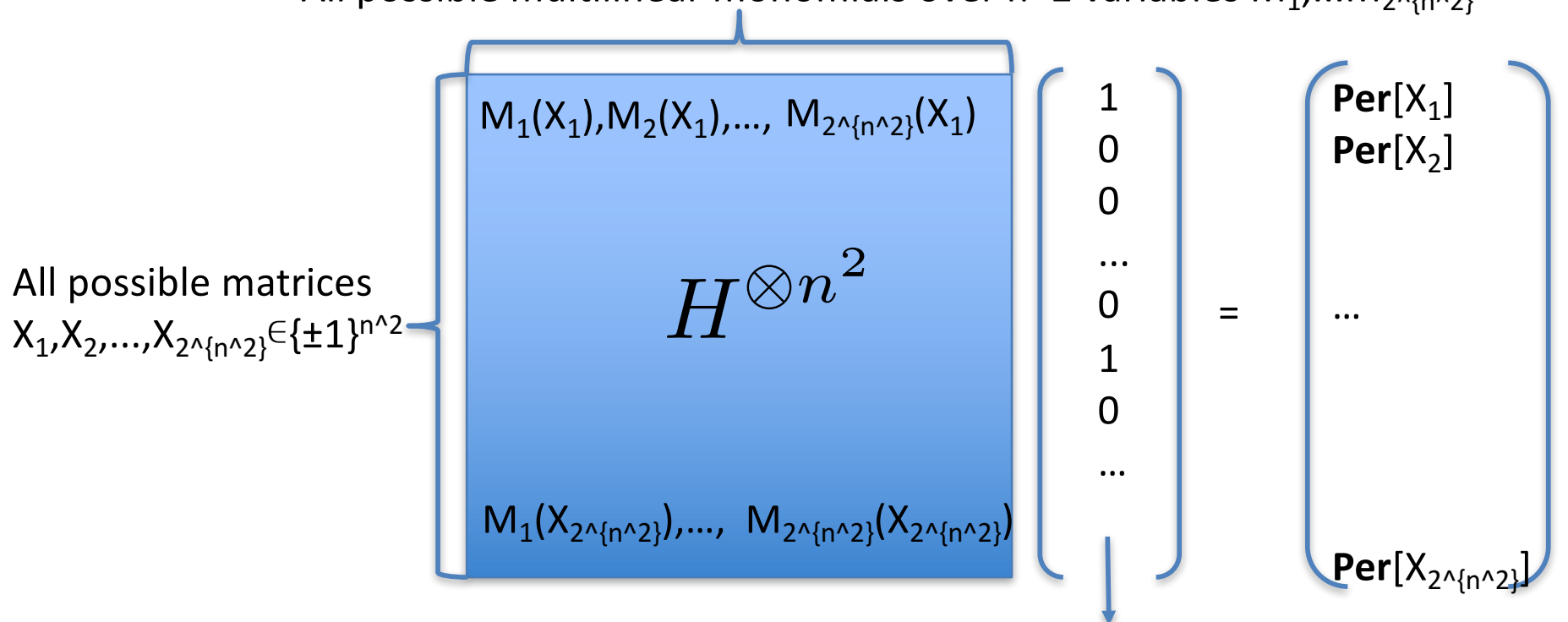
$$\frac{1}{\sqrt{n!2^{n^2}}} \sum_{w \in \{0,1\}^{n^2}} \sum_{\sigma \in S_n} (-1)^{\langle w, h(\sigma) \rangle} |w\rangle \quad 2$$

This is the permanent of $\{\pm 1\}^{n \times n}$ matrix encoded by the string w

What's happening?

- Recall, **Permanent**(x_1, x_2, \dots, x_{n^2}) is a multilinear polynomial of degree n
- Our quantum sampling algorithm (*omitting normalization*):

All possible multilinear monomials over n^2 variables $M_1, \dots, M_{2^{n^2}}$



This is supported on the monomials in the **Permanent**
 Heilbronn QISoP Quantum Algorithms Meeting, Cambridge University

Approximate sampler consequences

- This is extremely similar to the hardness consequence for Aaronson and Arkhipov: except their matrix distribution is iid Gaussian, $\mathcal{N}(0,1)$
- Suppose A is an approximate sampler for D_{PER} . But our “quantum sampler” is completely different!
 - Unlike exact case can't trust the sampler on any single probability
 - But, if A samples from distribution $\epsilon\delta$ far from D_{PER} we know:
 - “Most probabilities in A 's distribution must be close to probabilities in D_{PER} ”
 - At least $(1-\delta)$ -fraction of probabilities must be within $\epsilon/2^{n^2}$ of true probability
 - *Strategy*: Choose a $Z \in \{-1, +1\}^{n^2}$ matrix with iid uniformly distributed entries and approximate its probability using Stockmeyer's algorithm
- We'd obtain solution that “solves $\text{Per}^2(X)$ ” in Σ_3 with two major caveats:
 - Only “works” with probability $1-\delta$ over choice of matrix
 - “Works” means approximating within additive error $\pm\epsilon n!$
 - **Our question**: How hard is this?
 - If it's $\#P$ -hard, by Toda's theorem, an approximate sampler for D_{PER} would imply a **PH collapse (as in the exact case)**

Relating Additive to Multiplicative error

- Our procedure computes:
 - $\text{Per}^2[X] \pm \epsilon n!$ with probability $1-\delta$ in Σ_3 -time $\text{poly}(n, 1/\epsilon, 1/\delta)$ time
- This is unnatural! Would like multiplicative error:
 - $(1-\epsilon)\text{Per}^2[X] \leq \alpha \leq (1+\epsilon)\text{Per}^2[X]$ with probability $1-\delta$ in Σ_3 -time $\text{poly}(n, 1/\epsilon, 1/\delta)$ time
- Can we get *multiplicative* error using our procedure?
 - “Permanent Anti-concentration conjecture” [AA’11]
 - Need: exists polynomial p so that for all n and δ
 - $\Pr_X[|\text{Per}(X)| < \sqrt{n!}/p(n, 1/\delta)] < \delta$
 - This may actually be true!!
 - For Bernoulli distributed $\{-1, +1\}^{n \times n}$ matrices:
 - $\forall \epsilon > 0 \Pr_X[|\text{Per}[X]|^2 < n!/n^{\epsilon n}] < 1/n^{0.1}$ [Tao & Vu ‘08]

How hard is “Approximating” the Permanent?

- *Scenario 1:*
 - Suppose I had a box that:
 - “Solves all the Permanents approximately”
 - Input: $\epsilon > 0$ and matrix $X \in \{-1, +1\}^{n \times n}$
 - Output: α so that:

$$(1 - \epsilon)\text{Per}^2(X) \leq \alpha \leq (1 + \epsilon)\text{Per}^2(X)$$
 - In time $\text{poly}(n, 1/\epsilon)$
 - This is **#P**-hard!
 - Proof: “Padding and binary search!”
- *Scenario 2:*
 - Suppose I had a box that:
 - “Solves most of the Permanents exactly”

$$\Pr_X[\alpha = \text{Per}^2[X]] > 1 - \delta$$
 - For $\delta = 1/\text{poly}(n)$
 - This is **#P**-hard!
 - Proof idea: Polynomial interpolation [Lipton '89 in finite field case...]
- Our “solution” has weakness of both Scenario 1 and 2
 - Hardness proofs break-down!
 - This is exactly the same reason other two “approximate” sampling results need conjectures...

Generalizations

- Entries of Matrix
 - Replace Quantum Fourier Transform over $Z_2^{n^2}$ with Quantum Fourier Transform over $Z_k^{n^2}$
 - Resulting amplitudes proportional to Permanents of matrices with entries of evenly-spaced points around unit circle
- Generalizing the distribution over matrices
 - Can recapture the Gaussian distributed entries of [AA'11]...
- “Hard Polynomial”
 - Generalize Permanent to any *Efficiently Specifiable* polynomial sampling
 - Multilinear, homogenous polynomials with m monomials of the form:
$$Q(X_1, X_2, \dots, X_n) = \sum_{y \in [m]} X_1^{h(y)_1} X_2^{h(y)_2} \dots X_n^{h(y)_n}$$
 - Where h is efficiently computable map (and h^{-1} is also)
 - Examples:
 - Permanent, Hamiltonian Cycle polynomial, many more...

Relation to other work

- There are lots of “exact” sampling results
 - Starting with [DiVincenzo-Terhal’02] and [Bremner-Jozsa-Shepherd’10]
 - These distributions can often be sampled by restrictive classes of quantum samplers
 - Constant depth quantum circuits [DT’02]
 - Quantum computations with commuting gates [BJS’10]
 - One clean qubit [Morimae et. al. 2014]
 - Etc...
- “Approximate” sampling is far less understood...
 - “Boson Sampling” [Aaronson and Arkhipov ’11]
 - “IQP Sampling” [Bremner, Montanaro and Shepherd’15]
 - Quantum Fourier Sampling [F., Umans ’15]
- All rely on similar non-standard hardness assumptions
 - Need to conjecture that computing “average-case approximate” solution to some polynomial is hard for the **PH**
 - Permanent [AA’11]
 - The partition function of a random instance of an Ising model [BMS’15]
 - Any *Efficiently Specifiable* polynomial [F., Umans ’15]

Thanks!