PRS (wrapup)
Pseudorandom Unitanies \& Unitary $t$-designs

## RECAP PRS construction

$\left|\psi_{f}\right\rangle=\frac{1}{\sqrt{2^{n}}} \sum_{x \in\{0,1\}^{n}}(-1)^{f(x)}|x\rangle$ where $f:\{0,1\}^{n} \rightarrow\{0,1\}$ is a uniformly random boolean function
Replace $f$ with $t$-wise independent function to get a $t$-design and with a pseodorandom function to get a Pseudurandom state family

Theorem $\left|\Psi_{f}\right\rangle$ is a $O\left(\frac{t^{2}}{2^{n}}\right)$-approximate $t$-design in trace distance.
ie. $\quad \| \mathbb{E}\left|\psi_{f} X \psi_{f}\right|^{\otimes t}-\mathbb{E}_{|\psi\rangle \sim H a a r} \left\lvert\, \psi X\left\langle\left.\psi\right|^{\otimes t} \|_{1} \leqslant \frac{t^{2}}{2^{n}}\right.$. \right.

Symmetric Subspace

$$
\left.\operatorname{Sym}_{d, t}=\left\{|\psi\rangle \in\left(\mathbb{C}^{d}\right)^{\nabla t}\left|R_{\sigma}\right| \psi\right\rangle=|\psi\rangle \text { for all } \sigma \in S_{t}\right\}
$$

Fact $\mathbb{E}_{\mid \psi)_{\sim \text { Haar }}} \left\lvert\, \psi X\left(\left.\psi\right|^{\otimes t}=\frac{\pi_{s y m_{d, t}}}{\operatorname{dim}\left(\pi_{s y m_{d, t}}\right)}\right.$ where $\pi_{\text {sym }_{d, t} \text { is the }}^{\text {projector on symd,t }}$ in \right.
$:=\rho_{\text {sym }}$ This is the maximally mixed state on the symmetric subspace
Thus, our task boils down to showing

$$
\mathbb{E}_{f}\left|\Psi_{f} X \Psi_{f}\right|^{\otimes t} \approx \rho_{s y m}
$$

In order to do this, let us give an explicit basis for the symmetric subspace
Basis for symmetric subspace For a computational basis state $\left|x_{1}, \ldots x_{t}\right\rangle$ where each $x_{i} \in[d]$, define the following symmetrization operation

$$
\left.\mid \operatorname{sym}\left(x_{1}, \ldots x_{t}\right)\right)=\frac{1}{\sqrt{t!}} \sum_{\sigma} R_{\sigma}\left|x_{1} \ldots x_{t}\right\rangle
$$

Example $|\operatorname{sym}(1,2,3)\rangle$

$$
\begin{aligned}
& \operatorname{sym}(3,2,1)\rangle=\frac{|123\rangle+|132\rangle+|213\rangle+|321\rangle+|231\rangle+|312\rangle}{\sqrt{6}} \\
& |\operatorname{sym}(1,1,2)\rangle=|\operatorname{sym}(2,1,1)\rangle=\cdots=\frac{|112\rangle+|211\rangle+|121\rangle}{\sqrt{3}}
\end{aligned}
$$

The collection of all such distinct vectors give an orthonormal basis for Sym dit
(We won't prove it here)

How many such vectors are there? The vectors correspond to "types"
If all $x_{1} \ldots x_{t}$ are distinct, $\#$ vectors $=\binom{d}{t}$
If some of them are 1 's, some are $2^{\prime} s, \ldots . \&$ and $s 0$ on
In general, a type of a vector is given by $\left(c_{1}, \ldots c_{d}\right)$ where $c_{i} \geqslant 0$ are integers and $\sum_{c_{i}}=t$

Total \# of vectors $=\operatorname{dim}\left(\right.$ Sym $\left._{d, t}\right)=\#$ of solutions to $\sum c_{i}=t$ with $c_{i} \geqslant 0$

$$
=\binom{d+t-1}{t-1}
$$

The "distinct" types correspond to having some $t$ out of $d c_{i}$ 's being I's and rest being o's.

The span of these vectors will play a key role, so let us define Sym^Dist to be the subspace spanned by there rectors and PsymnDist to be the maximally mixed state on this subspace

Note that the bulk of the symmetric subspace is made by the distinct vectors since

$$
\begin{aligned}
\frac{\binom{d}{t}}{\binom{d+t-1}{t-1}} \geqslant \frac{\binom{d}{t}}{\binom{d+t}{t}}=\frac{\frac{d!}{t!(d-t)!}}{\frac{(d+t)!}{t!d!}} & =\frac{d(d-1) \cdots(d-t+1)}{(d+t) \cdots(d+1)} \\
& \geqslant \frac{(d-t)^{t}}{(d+t)^{t}} \\
& =\left(1-\frac{t}{d}\right)^{t} \\
& \geqslant 1-o\left(t^{2} / d\right)
\end{aligned}
$$

This easily implies the following claim (whose details are left to exerciser)
Claim 1 $\| \rho_{s y m}-\rho_{\text {sym } ~}$ Dist $\|_{1} \leqslant t^{2} / d$
To complete the proof of the theorem, we shall sketch a proof of the following
Claim $2\left\|\mathbb{E}_{f}\left|\psi_{f} X \psi_{f}\right|^{\otimes t}-\rho_{\text {symnDist }}\right\|_{1} \leqslant t^{2}$
Together these imply that $\left\|\mathbb{E}_{f}\left|\psi_{f} X \psi_{f}\right|^{\otimes t}-\rho_{s y m}\right\|_{1} \leqslant t^{2} d$

Proof sketch for Claim 2 Recall that $\left.\left.\left|\psi_{f}\right\rangle=\frac{1}{\sqrt{d}} \sum_{x \in[d]}(-1)^{f(x)} \right\rvert\, x\right)$ where $d=2^{n}$

$$
\left.\left.\mid \psi_{f}\right)^{\infty t}=\frac{1}{\sqrt{d t}} \sum_{x_{1} \ldots x_{t} \in[d]^{t}}(-1)^{f\left(x_{1}\right)}(-1)^{f\left(x_{2}\right)} \ldots . \mid x_{1}, \ldots x_{t}\right):=\frac{1}{\sqrt{d t}} \sum_{\vec{x} \in[d]^{t}}(-1)^{f(\vec{x})}|\vec{x}\rangle
$$

Moreover, permuting the $t$ registers does not change the state, so,

$$
\begin{align*}
& \mathbb{E}_{\sigma} R_{\sigma}\left|\psi_{f}\right\rangle^{\otimes t}=\left|\psi_{f}\right\rangle^{\otimes t} \\
& \text { and } \mathbb{E}_{f} \mid \psi_{f} X \psi_{f}^{\beta t}=\mathbb{E}_{\sigma} R_{\sigma}\left(\mathbb{E}_{f}\left|\psi_{f} X \psi_{f}\right|^{\otimes t}\right) \tag{*}
\end{align*}
$$



$$
\begin{aligned}
= & \frac{1}{d t} \sum_{\substack{\vec{x}_{1}, \vec{y} \\
\text { dis }}} \mathbb{E}_{1}^{\prime}\left[(-1)^{f(\vec{x})}(-1)^{f(\vec{y})}\right]|\vec{x} \times \vec{y}| \\
& +\frac{1}{d t} \sum_{\substack{\vec{x}, \vec{y} \\
\text { not dist. }}} \mathbb{E}^{[ }\left[(-1)^{f(\vec{x})}(-1)^{f(\vec{y})}\right]|\vec{x} X \vec{y}|
\end{aligned}
$$

In the first term, the expectation
for some permutation $\pi$ of $t$ elements

$$
\begin{align*}
\text { So, the first term } & =\frac{1}{d t} \sum_{\vec{x}} \sum_{\pi}|\vec{x} X \vec{x}| R_{\pi} \\
& =\frac{\sqrt{t!}}{d t} \sum_{\vec{x}}|\vec{x}\rangle\langle\operatorname{sym}(\vec{x})| \\
& \left.=\frac{\sqrt{t!}}{d t} \frac{1}{t!} \sum_{\sigma} R_{\sigma} \vec{x}\right\rangle\langle\operatorname{sym}(\vec{x})| \\
& =\frac{1}{d t} \sum_{\vec{x}}|\operatorname{sym}(\vec{x}) \times \operatorname{sym}(\vec{x})|=\frac{t!}{d t} \pi_{\text {sym }} \wedge \text { dist } \\
& =\frac{t!\binom{d}{t}}{d t} \rho_{\operatorname{sym} \wedge} \text { Dist } \approx \rho_{\text {sym }} \wedge \text { Dist } \quad \text { since } \frac{t^{\prime}\left(\frac{d}{t}\right)}{d t} \approx 1 \tag{3}
\end{align*}
$$

The contribution of all the non-distinct terms can be bounded by the fraction of such terms among all $d^{t}$ tuples. This is the probability of seeing a collision when drawing $t$ elements uniformly from [d] $\&$ is at most $t^{2} / d$

Thus, $\mathbb{E}_{f}\left|\psi_{f} X \psi_{f}\right|^{\otimes t}=\rho_{\text {sym }}$ Dist + err $\quad$ where $\|$ err $\|_{1} \leqslant t^{2} / d$

Pseudorandom Unitaries \& Unitary $t$-designs
A Haar random unitary on $n$-quits is a "uniformly random " $2^{n} \times 2^{n}$ Unitary matrix
The notion of unitary $t$-designs and pseudorandom unitaries are two different ways of derandomizing a Haar random unitary

Unitary t-design A distribution over $d \times d$ unitary matrices, where $d=2^{n}$, is called a unitary $t$-deign if for all $|\Psi\rangle$,

$$
\mathbb{E}_{\text {UNt-design }^{2}}
$$

$\langle\psi|\left\{\frac{I}{I-U_{I}^{+\oplus}}-U_{I}^{\otimes t}-\right\}|\psi\rangle \quad \approx \underset{U_{n} \text { Haar }}{\text { ET }}$

$$
\langle\psi|\left\{\left\{U_{I}^{a t}-U_{I}^{\theta t}-\right\}|\psi\rangle\right.
$$

In other words, given $t$ parallel applications of $U$ on the first register I (on nt-qubits), denoted by $U_{I}^{\otimes t}$, no procedure even efficient can distinguish the two. Here, $t$ is fixed beforehand

Note: A state $t$-design is just a weaker case of this, just take any unitary that maps $\left.10^{n}\right\rangle^{\theta t} \rightarrow|\phi\rangle^{\theta t}$ where $|\phi\rangle$ is a state $t$-design

Then, taking $\left.|\psi\rangle^{\otimes t}=10^{n}\right)^{\otimes t}$ above, we also get a state $t$-design from the above The guarantee above is for all states $(\psi)$ which make this a lot more challenging task

There are two notions of approximations that are usually considered
Additive Error This measures the error in the trace norm: $\forall|\psi\rangle$ we have

Multiplicative Error $\forall \mid \psi)$, we have


Note: Multiplicative error $t$-design also implies additive error $t$-design with the same $\varepsilon$ parameter, but the other way could increase the error paameter by $d^{o(t)}$ factor

Pseudorandom Unitary A family of $n$-quit unitaries $\left\{U_{k}\right\}_{k \in\{0,1\}^{n}}$ is called a pseudorandom unitary if
(1) Given $k \in\{0,1\}^{n}$, $U_{k}$ can be implemented in poly (n) time
(2) No poly-time distinguisher $A$ can query the unitary and distinguish a random $U_{k}$ from a Haar random unitary,

$$
\left|\mathbb{P}_{k \in\{0,1]^{n}}\left[A^{U_{k}}\left(1^{n}\right)=1\right]-\mathbb{P}_{U \sim \text { Haar }}\left[A^{U}\left(1^{n}\right)=1\right]\right| \leq \text { negro }(n)
$$



If the distinguisher $A$ is only allowed to make parallel queries to the unitary, we say its a non-adaptive PRU. Such an algorithm $A$ is given by


Note that the corresponding mixed states before measurement are


This is almost the same as a $t$-design but here $t=$ poly $(n)$ is not known in advance

Note: PRUs imply PRS similar to what we discussed before for $t$-design

## Applications \& Constructions

A random quantum circuit of large enough depth gives a $t$-design and there are interestingapplications in random circuit sampling. One of the focus of $t$ design construction is to get a very efficient construction of $t$-designs with small size and depth

One can also conjecture that a random quantum circuit of poly(n) depth is a PRU but if we could prove this without any assumption, we would show that $B Q P \neq P S P A C E$ Up until recently, there was no known construction for a PRU but in a recent paper of mine with Metger, Poremba and Yen, we showed" that the following simple construction giver a PRU as well as a Unitary $t$-design (Caveat: in the current version, we have an isometry that maps $n$ to $n+\log ^{2} n$ quits instead of a unitary mapping $n$ to $n$ quits)

## Construction

Let $c$ be any unitary 2-design (exact constructions are known for $t=2$ )
Let $P=\sum_{x \in\{0,1\}^{n}}|x| x(x) \mid$ be a random permutation matrix $\left(\pi\right.$ is a randoin permutation of $\left.\{0,1\}^{h}\right)$
Let $F=\sum_{x \in\left\{0,13^{n}\right.}(-1)^{f(x)}|x| x \mid$ be a random $\pm 1$ diagonal matrix ( $f$ is uniformly random boolean function)

Then, $U=$ PFC

- is a pseudorandom unitary if we replace $F \& P$ with pseudorandom functions \& permutations


## (additive error)

- is a $t$-design if we replace them with their $t$-wise independent versions.

This gives a simple and more efficient $t$-design construction.
Open problem Find interesting applications of PRUS
Currently the biggest motivation comes from studying- black holes where PRUs are used to model black hole dynamics so that the black hole can efficiently do it but the output looks Haar random to every feasible experiment that can be done

