# Privacy and Communication Complexity 

The Hardness of Being Private [ACC ${ }^{+} 12$ ]

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A submatrix is monochromatic if $f$ is constant on inputs in the submatrix.
A deterministic protocol computing $f$ repeatedly partitions $M_{f}$ into rectangles (submatrices) until every rectangle is monochromatic.

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## Vickrey auction

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|  | 1 | 2 | 3 | 4 | $\ldots$ | $2^{n}-1$ | $2^{n}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | $(1, B)$ | $(1, B)$ | $(1, B)$ | $(1, B)$ | $\ldots$ | $(1, B)$ | $(1, B)$ |
| 2 | $(1, A)$ | $(2, B)$ | $(2, B)$ | $(2, B)$ | $\ldots$ | $(2, B)$ | $(2, B)$ |
| 3 | $(1, A)$ | $(2, A)$ | $(3, B)$ | $(3, B)$ | $\ldots$ | $(3, B)$ | $(3, B)$ |
| 4 | $(1, A)$ | $(2, A)$ | $(3, A)$ | $(4, B)$ | $\ldots$ | $(4, B)$ | $(4, B)$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ | $\vdots$ |
| $2^{n}-1$ | $(1, A)$ | $(2, A)$ | $(3, A)$ | $(4, A)$ | $\ldots$ | $\left(2^{n}-1, B\right)$ | $\left(2^{n}-1, B\right)$ |
| $2^{n}$ | $(1, A)$ | $(2, A)$ | $(3, A)$ | $(4, A)$ | $\ldots$ | $\left(2^{n}-1, A\right)$ | $\left(2^{n}, B\right)$ |
|  |  |  |  |  |  |  |  |

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| ! |  |  |  |  |  |  |  |
| $2^{n}-1$ | $(1, A)$ | $(2, A)$ | $\begin{aligned} & (3, A) \\ & (3, A) \end{aligned}$ | $\begin{aligned} & (4, A) \\ & (4, A) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline \ldots \\ \ldots \\ \hline \end{array}$ | $\left(2^{n}-1, B\right)$ | $\left(2^{n}-1, B\right)$ |
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Regions (preimages)
region $R_{x, y}=$ $\left\{\left(x^{\prime}, y^{\prime}\right) \in X \times Y \mid\right.$ $\left.f(x, y)=f\left(x^{\prime}, y^{\prime}\right)\right\}$
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## Rectangles

rectangle $P_{x, y}=$ $\left\{\left(x^{\prime}, y^{\prime}\right) \in X \times Y \mid\right.$ $f(x, y)=f\left(x^{\prime}, y^{\prime}\right)$
and
$\left.\pi(x, y)=\pi\left(x^{\prime}, y^{\prime}\right)\right\}$
defined by protocol

## Privacy against eavesdroppers

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Alice's first move? NO, loses privacy for Alice!

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Alice's only choice for a privacy-preserving first message.

## Privacy against eavesdroppers

Can an eavesdropper learn about $x$ and $y$, aside from $z=f(x, y)$ ?


Bob's only privacy-preserving first message.

## Privacy against eavesdroppers

Can an eavesdropper learn about $x$ and $y$, aside from $z=f(x, y)$ ?

... and so on ...

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Ascending English bidding is the only perfectly private protocol. Lengthy!

## Perfect privacy

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## Characterizing perfect privacy [Kus89]

The perfectly private functions of 2 inputs are fully characterized combinatorially. A private deterministic protocol for such functions is given by "decomposing" $M_{f}$.

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But perfect privacy is unattainable for many functions! This leads us to a relaxation...

## Approximate privacy

Let's relax our requirement from one big rectangle to simply grouping inputs in the same preimage into largeish rectangles.

## Approximate privacy

Privacy approximation ratio [FJS10]
A protocol for $f$ has worst-case privacy approximation ratio:

$$
\text { worst-case PAR }=\max _{(x, y)} \frac{\left|R_{x, y}\right|}{\left|P_{x, y}\right|}
$$

average-case $\operatorname{PAR}=\mathbb{E}_{(x, y)} \frac{\left|R_{x, y}\right| \mathcal{U}}{\left|P_{x, y}\right| \mathcal{U}}$ over distribution $\mathcal{U}$

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$$
\begin{aligned}
& \text { worst-case } \mathrm{PAR}=10 \\
& \text { average-case } \mathrm{PAR}=2
\end{aligned}
$$

## Two-player Vickrey auction

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## Upper bounds for Vickrey auctions [FJS10]

|  | English bidding | bisection protocol |
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| communication cost | $2^{n}$ | $O(n)$ |
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## Worst-case lower bound (our work)

For all $n$, for all $p, 2 \leq p \leq n / 4$, any deterministic protocol for the $n$-bit two-player Vickrey auction obtaining PAR less than $2^{p-2}$ has length at least $2^{n / 4 p}$.

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For all $n, r \geq 1$, any deterministic protocol of length at most $r$ for the $n$-bit two-player Vickrey auction has average-case PAR greater than $\Omega\left(\frac{n}{\log (r / n)}\right)$.

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These are trade-offs: good privacy for short communication.

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The proof proceeds as follows.
Fix any protocol $\pi$ for Vickrey auction.
This proof will find some input pair $(x, y)$ which either

- loses enough privacy (has $\operatorname{PAR}_{x, y}(\pi) \geq 2^{p-2}$ ), or
- takes communication at least $2^{n / 4 p}$ in protocol $\pi$.

We'll track the "small" inputs $(x, y)$ from the upper left-hand corner:

$$
\left\{(x, y) \mid x, y \leq 2^{n-p}\right\}
$$

These inputs stand to lose the most privacy.

The rest of the inputs will be called "large."


## Let $v$ be some vertex in the protocol tree for $\pi$.

- inputs which reach node $v$ :

$$
T(v)=T_{A}(v) \times T_{B}(v)=\{(x, y) \mid \text { input }(x, y) \text { reaches } v \text { during } \pi\}
$$

- the square of small inputs $S(v) \times S(v)$ which reach $v$ :

$$
S(v)=T_{A}(v) \cap T_{B}(v) \cap\left[2^{n-p}\right]
$$

- the "large" inputs for each player:

$$
\begin{aligned}
& A^{L}(v)=T_{A}(v) \cap\left\{2^{n-p}, \ldots, 2^{n}-1\right\} \\
& B^{L}(v)=T_{B}(v) \cap\left\{2^{n-p}, \ldots, 2^{n}-1\right\}
\end{aligned}
$$

We want a square of small inputs which reach $v$ because every square of inputs resembles the entire Vickrey auction (has no quick, private protocol).

## At root node $r$ :

- $T_{A}(r)=T_{B}(r)=\left[2^{n}\right]$
- $S(r)=\left[2^{n-p}\right]$
- $A^{L}(r)=B^{L}(r)=\left\{2^{n-p}, \ldots, 2^{n}-1\right\}$


## Inputs only lose privacy as the protocol continues.

For any node $v$ in the protocol tree and any $(x, y) \in T(v)$,

$$
\operatorname{PAR}_{x, y}(\pi)=\frac{\left|R_{x, y}\right|}{\left|P_{x, y}\right|} 0 \geq \frac{\left|R_{x, y}\right|}{\left|R_{x, y} \cap T(v)\right|}=\operatorname{PAR}_{x, y}^{v}(\pi)
$$

In particular, consider some $(x, y) \in T(v)$ where $x>y$ (Alice wins).

$$
\begin{equation*}
\operatorname{PAR}_{x, y}(\pi) \geq \operatorname{PAR}_{x, y}^{v}(\pi) \geq \frac{2^{n}-2^{n-p}}{\left|A^{L}(v)\right|+2^{n-p}} \tag{1}
\end{equation*}
$$

Set $\alpha=1-2^{-n / 4 p}$.

## Our strategy for finding $(x, y)$

(1) Start at the root with $S(r), A^{L}(r)$, and $B^{L}(r)$ as defined.
(2) At node $v$, say it's Alice's turn to speak (the case is symmetric for Bob). Alice sends bit $b$ which partitions $T_{A}(v)$ into two pieces, inducing partitions of $S(v)$ and $A^{L}(v)$.

- progress: if

$$
(1-\alpha)|S(v)| \leq\left|S_{0}(v)\right| \leq \alpha|S(v)|
$$

then follow the branch such that $\left|A_{i}^{L}(v)\right| \leq \frac{1}{2}\left|A_{i}^{L}(v)\right|$.

- useless: if for some $i$,

$$
\left|S_{i}(v)\right| \geq \alpha|S(v)|
$$

then follow that branch of the protocol tree.
(3) Repeat step 2 until one player has made $p$ progress steps, or $v$ is a leaf.

Progress steps make the protocol short-but-not-private (bisection-like); useless steps make the protocol private-but-not-short (English-like).

## Case 1: Alice makes $p$ progress steps (WLOG - symmetric for Bob)

We know that:

- $\left|R_{x, y}\right| \geq 2^{n}-2^{n-p}$ for every $(x, y) \in S(v) \times S(v)$
- $\left|A^{L}(r)\right|=2^{n}-2^{n-p}$

For every progress step Alice made from vertex $u$ to $w$ in the protocol, we know that $\left|A^{L}(w)\right| \leq \frac{1}{2}\left|A^{L}(u)\right|$. Thus $\left|A^{L}(v)\right| \leq \frac{1}{2^{p}}\left|A^{L}(r)\right|$.
Thus for any $(x, y) \in S(v) \times S(v)$, by equation (1)

$$
\operatorname{PAR}_{x, y}^{v}(\pi) \geq \operatorname{PAR}_{x, y}(\pi) \geq \operatorname{PAR}_{x, y}^{v}(\pi) \geq \frac{2^{n}-2^{n-p}}{\left|A^{L}(v)\right|+2^{n-p}} \geq 2^{p-2}
$$

## Case 2: We reach a leaf $v$, so $|S(v)|=1$

Let $q$ be the total number of useless steps made. Fewer than $2 p$ progress steps were made. $|S(r)|=2^{n-p}$.

$$
1=|S(v)| \geq 2^{n-p}(1-\alpha)^{2 p} \alpha^{q}
$$

Thus $q \geq 2^{n / 4 p}$.

## Privacy against players

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## Subjective regions

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\begin{gathered}
\text { region } R_{x, y}^{A}= \\
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defined by function Alice sees


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| 0 |  |  |
| :--- | :--- | :--- |
| 0 | 1 |  |
| 0 | 1 |  |
| 0 | 1 |  |
| 0 | 1 |  |

## Subjective rectangles

$$
\begin{aligned}
& \text { rectangle } P_{x, y}^{B}= \\
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| :--- | :--- | :--- |
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Subjective privacy approximation ratio (Feigenbaum Jaggard Schapira '10)

$$
\text { average-case } \mathrm{PAR}^{\text {sub }}=\max _{v=A, B} \mathbb{E}_{(x, y)} \frac{\left|R_{x, y}^{v}\right|}{\left|P_{x, y}^{v}\right|}
$$

Information cost (Braverman et al.)

$$
\left.I C_{\mu}(\pi)=I(\mathbf{X}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y})+I(\mathbf{Y}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{X})\right\}
$$

## Informational privacy (Klauck ’02)

$\operatorname{PRIV}_{\mu}(\pi)=\max \{I(\mathbf{X}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y})), I(\mathbf{Y}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{X}, f(\mathbf{X}, \mathbf{Y}))\}$

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Theorem (us '12): $\operatorname{PRIV}_{\mu}(P) \leq \log \left(\operatorname{avg}_{\mu} \operatorname{PAR}^{\text {sub }}(P)\right)$
Theorem (Braverman '11): $\mathrm{IC}_{\mathcal{U}}($ DISJ $)=\Omega(n)$.

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\left.I C_{\mu}(\pi)=I(\mathbf{X}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y})+I(\mathbf{Y}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{X})\right\}
$$

## Informational privacy (Klauck '02)

$$
\operatorname{PRIV}_{\mu}(\pi)=\max \{I(\mathbf{X}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y})), I(\mathbf{Y}: \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{X}, f(\mathbf{X}, \mathbf{Y}))\}
$$

Theorem (us '12): $\operatorname{PRIV}_{\mu}-\log |Z| \leq I C \leq 2\left(\operatorname{PRIV}_{\mu}+\log |Z|\right)$
Theorem (us '12): $\operatorname{PRIV}_{\mu}(P) \leq \log \left(\operatorname{avg}_{\mu} \operatorname{PAR}^{\text {sub }}(P)\right)$
Theorem (Braverman '11): $\mathrm{IC}_{\mathcal{U}}($ DISJ $)=\Omega(n)$.

## Theorem 3

Any protocol $P$ computing the $n$-bit Set Intersection INTERSEC $_{n}$ has exponential average-case subjective PAR:

$$
\operatorname{avg}_{\mathcal{U}} \operatorname{PAR}^{\mathrm{sub}}(P)=2^{\Omega(n)}
$$

## Observation

For a region $R$, define $\operatorname{cut}_{\pi}(R)=\left|\left\{P_{x, y} \mid(x, y) \in R\right\}\right|$.

$$
\begin{aligned}
\operatorname{avg} \operatorname{PAR}_{\mu}(\pi) & =\mathbb{E}_{\mu} \frac{\left|R_{x, y}\right|}{\left|P_{x, y}\right|}=\sum_{(x, y) \in X \times Y} \mu(x, y) \frac{\left|R_{x, y}\right|}{\left|P_{x, y}\right|} \\
& =\sum_{R \text { region }} \sum_{(x, y) \in R} \mu(x, y) \frac{|R|}{\left|P_{x, y}\right|} \\
& =\sum_{R \text { region }}|R|\left(\sum_{(x, y) \in R} \frac{\mu(x, y)}{\left|P_{x, y}\right|}\right. \\
& =\sum_{R \text { region }}|R| \cdot \operatorname{cut}_{\pi}(R)
\end{aligned}
$$

Theorem (us '12): $\operatorname{PRIV}_{\mu}(P) \leq \log \left(\operatorname{avg}_{\mu} \operatorname{PAR}^{\text {sub }}(P)\right)$
Proof:

$$
\begin{aligned}
& \mathbf{I}(\mathbf{X} ; \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y})) \\
& =\mathbf{H}(\mathbf{X} ; \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y}))-\mathbf{H}(\mathbf{X} \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y}), \pi(\mathbf{X}, \mathbf{Y})) \\
& \leq \mathbf{H}(\mathbf{X} ; \pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}, f(\mathbf{X}, \mathbf{Y})) \\
& =\sum_{y, z} \operatorname{Pr}[\mathbf{Y}=y, \mathbf{Z}=z] \cdot \mathbf{H}(\pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}=y, f(\mathbf{X}, \mathbf{Y})=z) \\
& =\sum_{y, z}\left|R_{z} \cap \mathbb{X} \times\{y\}\right|_{\mu} \cdot \mathbf{H}(\pi(\mathbf{X}, \mathbf{Y}) \mid \mathbf{Y}=y, f(\mathbf{X}, \mathbf{Y})=z) \\
& =\sum_{y, z}\left|R_{z} \cap \mathbb{X} \times\{y\}\right|_{\mu} \cdot \log \left(\operatorname{cut}_{\pi}\left(R_{z} \cap X \times\{y\}\right)\right) \\
& \leq \log \sum_{y, z}\left|R_{z} \cap \mathbb{X} \times\{y\}\right|_{\mu} \cdot\left(\operatorname{cut}_{\pi}\left(R_{z} \cap X \times\{y\}\right)\right) \\
& \leq \log \left(\operatorname{avg} \operatorname{PAR}^{\text {sub }}(\pi)\right)
\end{aligned}
$$

# Next time: differential privacy. Yet another definition of privacy! 

## References

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