# Non-Interactive Secure Computation of Inner-Product from LPN and LWE 

Geoffroy Couteau, Maryam Zarezadeh

## Non-Interactive Key Exchange

A very appealing interaction pattern:

- $n$ parties simultaneously broadcast a single message
- All pairs of parties get a shared private key
- Avoids the $\Omega\left(n^{2}\right)$ overhead of naive pairwise exchange

Non-Interactive Secure Computation

## This Work



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## $K_{14} \leftarrow \operatorname{Key}\left(\mathrm{sk}_{1}, \mathrm{pk}_{4}\right)$ <br> 

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Can we get a similar pattern for some simple MPC?

- $n$ parties broadcast an encoding of their input
- Pairs $\left(P_{i}, P_{j}\right)$ can compute $f_{i}\left(x_{i}, x_{j}\right)$ and $f_{j}\left(x_{i}, x_{j}\right)$ from their state and the other party's encoding
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## This Work

- Non-interactive MPC for shares of inner products: $f_{i}\left(x_{i}, x_{j}\right), f_{j}\left(x_{i}, x_{j}\right)$ form shares of $\left\langle x_{i}, x_{j}\right\rangle$ over $\mathbb{F}$
- Reconstructing the result = sending a single element of $\mathbb{F}$
$f_{1}\left(x_{1}, x_{4}\right)=\operatorname{Out}\left(\operatorname{st}_{1}, \operatorname{Enc}\left(x_{4}\right)\right)$


[^0]Non-Interactive Inner Product: Applications
Inner products is a simple, but very useful function:

- Biometric authentication (via Hamming distance)
- Pattern matching (via Hamming distance)
- ML (k-nearest neighbours,SVM, rule mining...)
- Linear algebra
- Similarity measure
- Simple statistics
. ...

| $y_{1}$ | $y_{2}$ | $y_{3}$ |
| :---: | :---: | :---: |
|  |  | \% |
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## Toy Example: Biometrics

- $n$ clients and $m$ servers with a fingerprint stored.
- Ahead of time, each party publishes an encoding of its fingerprint.

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## Toy Example: Biometrics

- $n$ clients and $m$ servers with a fingerprint stored.
- Ahead of time, each party publishes an encoding of its fingerprint.
- Later, a client $C_{i}$ can authenticate to a server $S_{j}$ by locally computing and sending his share of the Hamming distance, a single element of $\mathbb{F}$.

Computes $\alpha_{s}=\operatorname{share}_{s}\left(\mathrm{HD}\left(x_{2}, y_{2}\right)\right)$


## Preliminaries: LPN and LWE

## LPN and LWE - Primal Form



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## LPN and LWE - Primal Form


$\operatorname{LPN}\left(\mathbb{F}_{2}\right): G \leftarrow_{\$} \mathbb{F}_{2}^{m \times n}, \quad \leftarrow_{\$} \mathbb{F}_{2}^{n}, \quad \leftarrow_{\$} \operatorname{Ber}\left(\mathbb{F}_{2}\right)^{n}$
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$\operatorname{LWE}\left(\mathbb{F}_{p}\right): G \leftarrow_{\$} \mathbb{F}_{p}^{m \times n}, \square \leftarrow_{\$} \mathbb{F}_{p}^{n}, \quad \leftarrow_{\$}[-B, B]^{n} \longleftarrow$ 'Small'

## Preliminaries: LPN and LWE

## LPN and LWE - Dual Form


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## Alekhnovich Key Exchange



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Embedding an Inner Product in Alekhnovich's Key Exchange


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Bob computes:
Alice computes:

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We are making progress - but $s$ has to be random for primal LPN to hold!

## Embedding an Inner Product in Alekhnovich's Key Exchange



How to embed Alice's input in $s$ ?

## Embedding an Inner Product in Alekhnovich's Key Exchange

Idea: split $H$ as $H_{0} \mid H_{1}$

$$
H \cdot{ }_{H_{0}} H_{H_{1}} \cdot{ }^{s_{0}}=H_{s_{1}} \cdot{ }^{s_{0}}+{ }_{H_{1}} \cdot{ }^{s_{1}}
$$

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## Multiparty Inner Product with Leakage

The protocol has $t^{2} / n$ correctness error.
! In MPC, correctness errors translate to leakage when a 'detectable' error occurs: the server learns an equation $\langle v, r\rangle$ with $v$ known and $r$ the noise vector.
$\Longrightarrow$ leaks $\approx N \cdot t^{2} / n$ linear equations in $r$ if the client interacts with $N$ servers.
$\Longrightarrow$ still secure under the LPN with leakage assumption (equivalent to standard LPN, but with a loss)


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## Alternatives

The above is fine when $N$ is not too large. For large $N$, or when overwhelming correctness matters (e.g. for biometric authentication), two alternatives:

1. We give an LWE-based variant with negligible error
2. We describe a way to remove errors via a sublinearcommunication preprocessing phase

| $y_{1}$ | $y_{2}$ | $y_{3}$ |
| :---: | :---: | :---: |
| ) |  | \% |
| ¢ | $\checkmark$ | ( $\downarrow$ |

Enc $\left(y_{1}\right)$
Enc $\left(y_{2}\right)$
$\operatorname{Enc}\left(y_{3}\right)$


## A Variant under LWE



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## A Variant under LWE



## A Variant under LWE



Rounding Lemma: if $q /(p \cdot|e|) \geq \lambda^{\omega(1)}$, then $\left\lceil(p / q) \cdot K^{\prime}\right\rfloor \bmod p$ and $\left\lceil(p / q) \cdot K^{\prime}\right\rfloor \bmod p$ form additive shares of $\langle x, y\rangle$ with proba $1-\operatorname{negl}(\lambda)$.

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## Removing Errors via Preprocessing

## Preprocessing phase



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Implementing the preprocessing

## Removing Errors via Preprocessing

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## Functionality

Samples $t$-sparse vectors $\left(r_{0}, r_{1}\right)$ and set $\left(s_{0}, s_{1}\right) \leftarrow \operatorname{Share}\left(\left\langle r_{0}, r_{1}\right\rangle\right)$

## Implementing the preprocessing


Then: $\left\langle r_{0}, r_{1}\right\rangle=\sum_{i=1}^{t} \sum_{j=1}^{t}\left\langle r_{0}^{(i)}, r_{1}^{(j)}\right\rangle=\sum_{i=1}^{t} \sum_{j=1}^{t}[\underbrace{k_{\sigma}^{(i)}={ }_{?} k_{\sigma}^{(j)}}_{\text {Secure Equality Test }}] \cdot \underbrace{v_{0}^{(i)} v_{1}^{(j)}}_{\text {OLE }}$
$\Longrightarrow s_{0}, s_{1}$ can be securely computed using $O\left(t^{2} \cdot \log n\right)$ communication

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## Implementing the preprocessing

$$
\text { Write } r_{\sigma}=\sum_{i=1}^{t} r_{\sigma}^{(i)} \text { where the } r_{\sigma}^{(i)} \text { are unit vectors } \underset{\substack{k_{\sigma}^{(i)}}}{0 \cdots 0} 0
$$

$$
\text { Then: }\left\langle r_{0}, r_{1}\right\rangle=\sum_{i=1}^{t} \sum_{j=1}^{t}\left\langle r_{0}^{(i)}, r_{1}^{(j)}\right\rangle=\sum_{i=1}^{t} \sum_{j=1}^{t}[\underbrace{k_{\sigma}^{(i)}={ }^{2} k_{\sigma}^{(j)}}_{\text {Secure Equality Test }}] \cdot \underbrace{v_{0}^{(i)} v_{1}^{(j)}}_{\text {OLE }}
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$\Longrightarrow s_{0}, s_{1}$ can be securely computed using $O\left(t^{2} \cdot \log n\right)$ communication
Improved version: using LPN with regular noise brings the cost down to $O(t \cdot \log n)$

## Malicious Security

In the malicious setting, Alice and Bob must prove that $\mathrm{pk}_{0}, \mathrm{pk}_{1}$ are well-formed


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We introduce a new efficient ZKPoK for LPN relations, with communication $O(t \cdot \log n)$

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ZK: knows a sparse $r_{0}$ such that $H_{0}^{\top} \cdot r_{0}=\mathrm{pk}_{0}^{0}$


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## Idea

Recent works on pseudorandom correlation generator show how to distribute shares of $\Delta \cdot r$ where $r \in \mathbb{F}_{p}^{n}$ is $t$-sparse, and $\Delta \in \mathbb{F}_{p^{k}}$, via function secret sharing (which exist under OWF) $\Longrightarrow$ we use these techniques to authenticate the noise vectors with a MAC $\Delta$ $\Longrightarrow$ we use the MAC to check the correct computation of the $\mathrm{pk}^{\prime} s$, al la SPDZ.

## Thank you for your attention!

## Questions?




[^0]:    $f_{1}\left(x_{1}, x_{4}\right)=\operatorname{Out}\left(\operatorname{st}_{4}, \operatorname{Enc}\left(x_{1}\right)\right)$

