## BetterTimes

## Privacy-assured Outsourced Multiplications for Additively

Homomorphic Encryption on Finite Fields


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- Privacy-preserving location proximity
- Privacy-preserving auctioning and bartering systems
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- Privacy-preserving auctioning and bartering systems
- Privacy-preserving voting
- Common assumption is honest-but-curious
- Many current solutions suffer
- Face recognition: Sadeghi et al. 2009, Erkin et al. 2009
- Location proximity: Zhong et al. 2007, Sedenka and Gasti 2014, Hallgren et al. 2015


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- Alice is the initiating party, and Alice receives the output
- Goal
- Bob learns nothing
- Alice learns at most the intended output


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- Multiplication: $\llbracket m_{1} \cdot m_{2} \rrbracket=\llbracket m_{1} \rrbracket \odot m_{2}$
- Blinding: given $\mathcal{M}^{\mathcal{U}}$ uniformly random distribution in $\mathcal{M} \backslash\{0\}$
- $\llbracket m \rrbracket \oplus \llbracket b \rrbracket=\llbracket r \rrbracket$, with $b, r \in \mathcal{M}^{\mathcal{U}}$
- $\llbracket m \rrbracket \odot \llbracket b \rrbracket=\llbracket r \rrbracket$, with $b, r \in \mathcal{M}^{\mathcal{U}}$


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- We solve this using outsourcing these multiplications through a novel protocol called BetterTimes.


## Communication Overview

- In our setting, protocols follow the form
- Alice initiates the protocol
- Bob sees only encrypted data (he can't decrypt)
- Possibly there are more round trips to finish the computation
- Bob responds with the final result



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(5) Bob computes $\llbracket a \rrbracket$ using all of $\llbracket x^{\prime} \rrbracket, \llbracket y^{\prime} \rrbracket, \llbracket z^{\prime} \rrbracket$ and $\llbracket a^{\prime} \rrbracket$

## BetterTimes communication

## Alice

## Bob



Figure: Visualization of the attested multiplication protocol

## Using BetterTimes in a formula

- Bettertimes assures that $\llbracket a \rrbracket$ is zero if and only if $\llbracket z \rrbracket=\llbracket x \cdot y \rrbracket$, and a uniformly random value otherwise.


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- Alice receives the correct output if and only if she computed all outsourced multiplications honestly, and a uniformly random value otherwise


## Private Evaluation of Arithmetic Formula

## Alice 10

## Bob



## Proof Outline for Privacy of Arbitrary Formula

Our Privacy definition follows the standard framework for secure multi-part computation (Lindell and Pinkas 2008)

## Theorem

For a fixed but arbitrary arithmetic formula $g(\vec{x}, \vec{y})$ represented by a recursive instruction $\iota \in$ Ins, for every adversary $\mathcal{A}$ against the protocol $\pi$ resulting from evaluate( $\iota$ ), there exist a simulator $\mathcal{S}$ such that:

$$
\left\{\operatorname{IDEAL}_{g, \mathcal{S}(s)}(\vec{x}, \vec{y})\right\} \xlongequal{\equiv}\left\{\operatorname{REAL}_{\pi, \mathcal{A}(s)}(\vec{x}, \vec{y})\right\}
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where $\xlongequal[\equiv]{c}$ denotes computational indistinguishability of distributions.

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- The full proof is given in the paper
- The theorem implicates that any protocol evaluating arithmetic formulas as defined in the paper can be evaluated in the presence of a malicious adversary while preserving privacy


## Benchmarks

- Performed benchmarks on prototype implementation in python
- Comparing to outsourced multiplications secure only against honest adversaries

Table: Times (in milliseconds) for outsourced multiplication

| Plaintext space | Time (in milliseconds) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | This approach | 1024 bits <br> Naive <br> approach | Extra work | This approach | 2048 bits Naive approach | Extra work |
| $2^{2}$ | 6.286 | 4.016 | 56.52\% | 29.686 | 19.458 | 52.56\% |
| $2^{8}$ | 6.400 | 4.017 | 59.32\% | 30.052 | 19.484 | 54.24\% |
| $2^{16}$ | 6.432 | 4.148 | 55.06\% | 30.188 | 19.574 | 54.22\% |
| $2^{24}$ | 6.538 | 4.100 | 59.46\% | 30.578 | 19.801 | 54.43\% |

- Benchmarks show that our more secure approach costs about 53-60\% extra work for a multiplication


## Protocols that can be secured with BetterTimes

- Several existing works can use the proposed approach to increase protection against malicious attackers
- Privacy-preserving face recognition: Sadeghi et al. 2009, Erkin et al. 2009
- Privacy-preserving location proximity: Zhong et al. 2007, Sedenka and Gasti 2014, Hallgren et al. 2015


## Conclusions

- Presented BetterTimes
- Using BetterTimes one can compute any arithmetic formula in the presence of a malicious Alice
- The overhead, compared to protection against honest adversaries, is about $55 \%$
- Of each multiplication, not of the formula as a whole
- Usually the number of multiplications is minimized, as additions are cheap with additively homomorphic encryption


## Thank you for your attention!

Questions?

