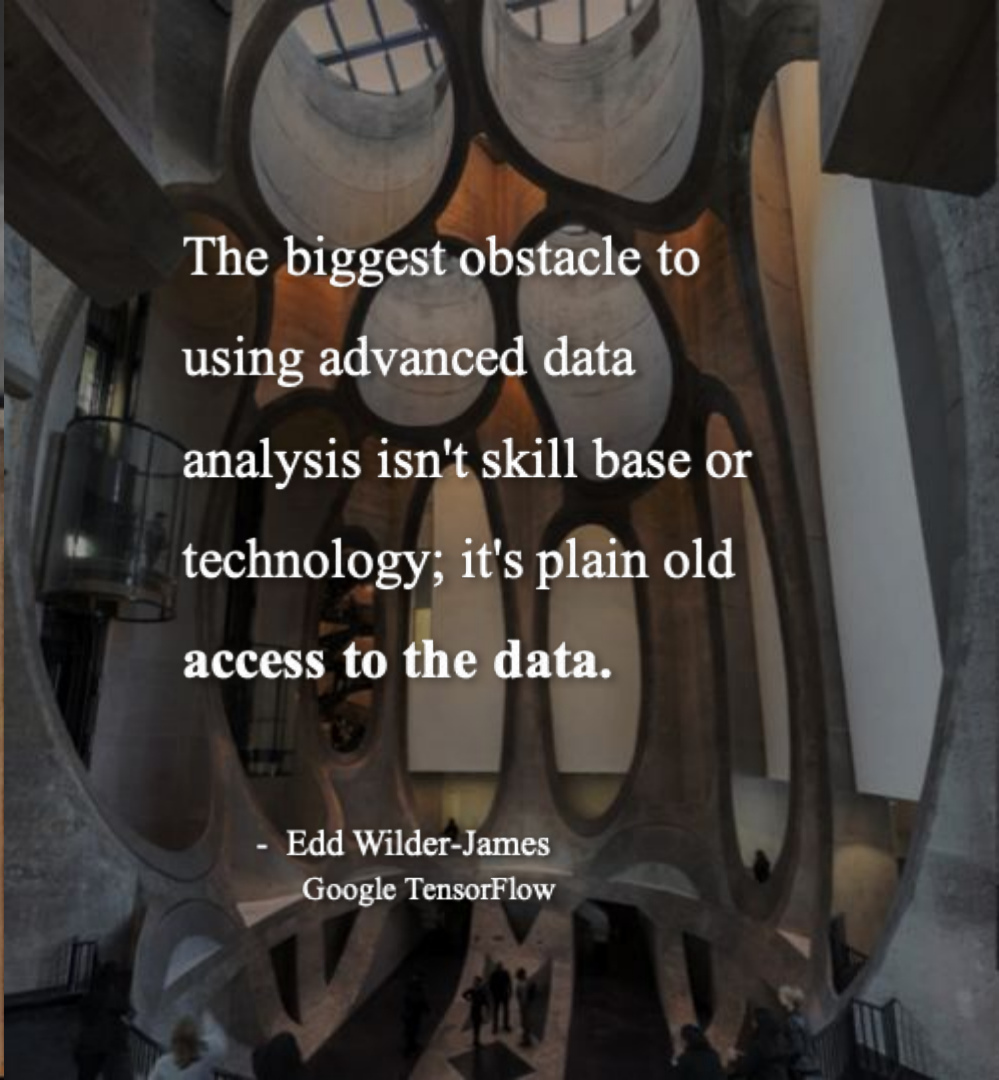


Scalable Privacy-Preserving Computing with High Numerical Precision

Dimitar Jetchev

Chief Technology Officer
Inpher Inc./Sarl





The biggest obstacle to using advanced data analysis isn't skill base or technology; it's plain old **access to the data.**

- Edd Wilder-James
Google TensorFlow

in transit

(<https://>)



at rest

(on disk)



in use

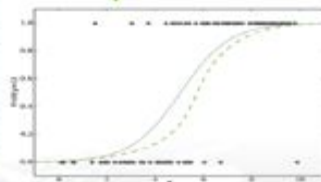
(in memory)



Opportunities beyond data security.

+ Governments

+ Organizations



Monetize analytics (without exposing data)

Access private data sources to train AI

Regulatory Compliance (GDPR, PDPA)

Cross-industry collaboration

Secure Cloud Computing

+ Jurisdictions

+ Departments

+ Datacenters



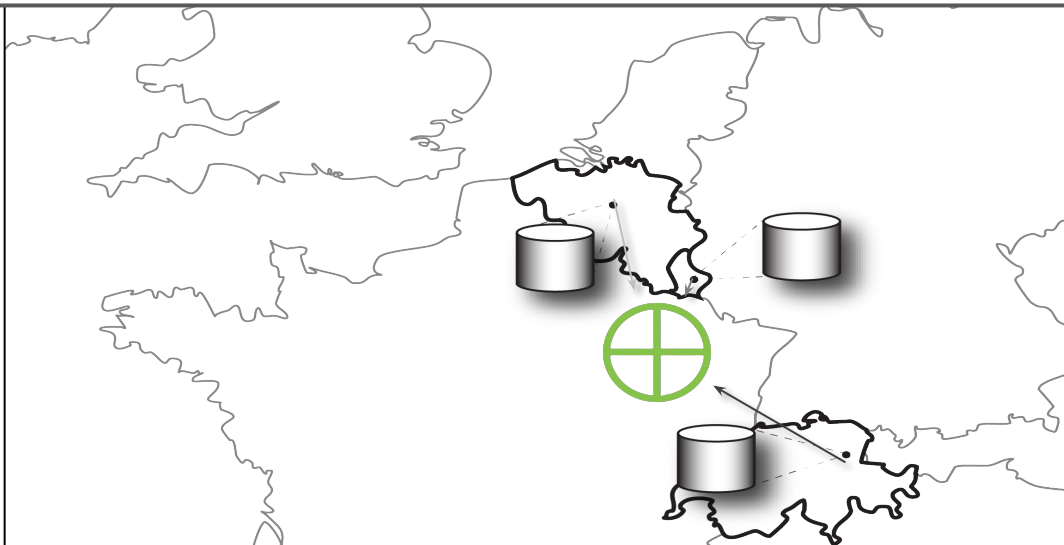


CIO JOURNAL



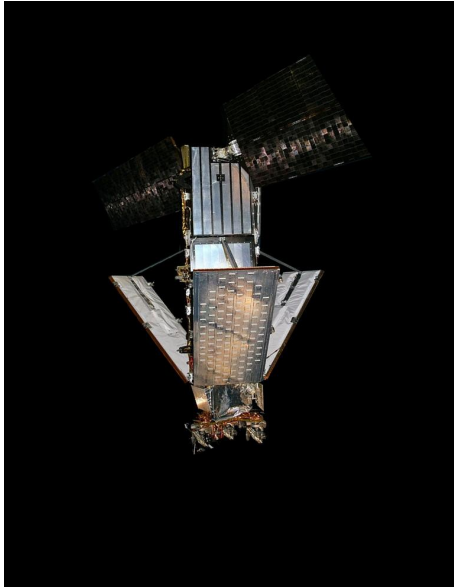
ING Belgium Sees Opportunities for 'Secret' Sharing of Encrypted Data

Zero-knowledge computing would let companies analyze encrypted information without revealing any secret information



High-Precision Use Cases

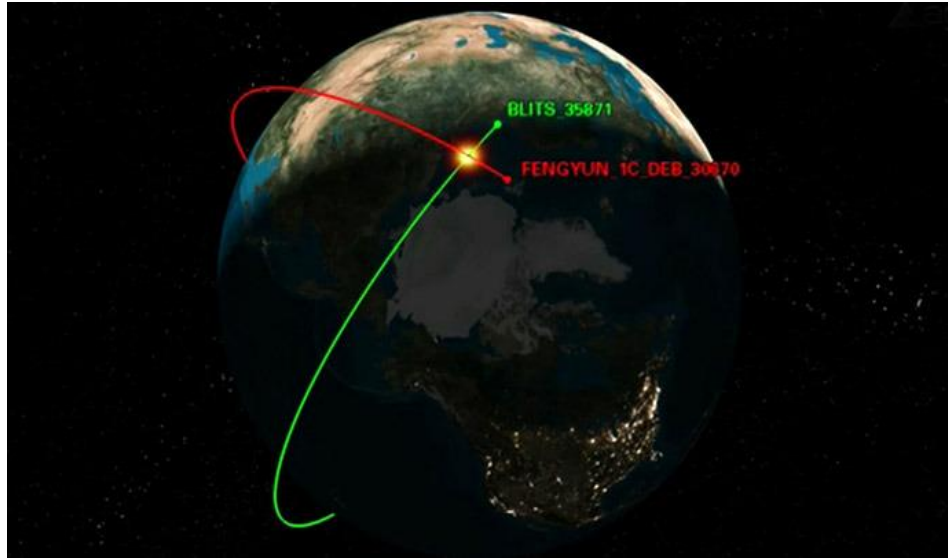
Iridium 33 and Kosmos-2251 Satellite Collision



- Collision - 2009
- 11,700 m/s
- 789 km above Syberia
- More than 2000 debris
- ISS special maneuvers



High-Precision Privacy-Preserving Compute



- Predicting collisions of satellites
- Satellite trajectories are private
- Satellite operators nonetheless perform **conjunction analysis**
- Need to evaluate non-linear functions with high numerical precision

Detecting Rare Events with Private Data

*see FC'18 paper: [High-Precision Privacy-Preserving Real-Valued Function Evaluation](#)

Problem: detect a rare event via a classification algorithm (e.g., a fraudulent activity or a rare market event)

- 1 out of 10,000 bank customers performs fraudulent activity
- A classifier predicting always negative has **99,99%** accuracy

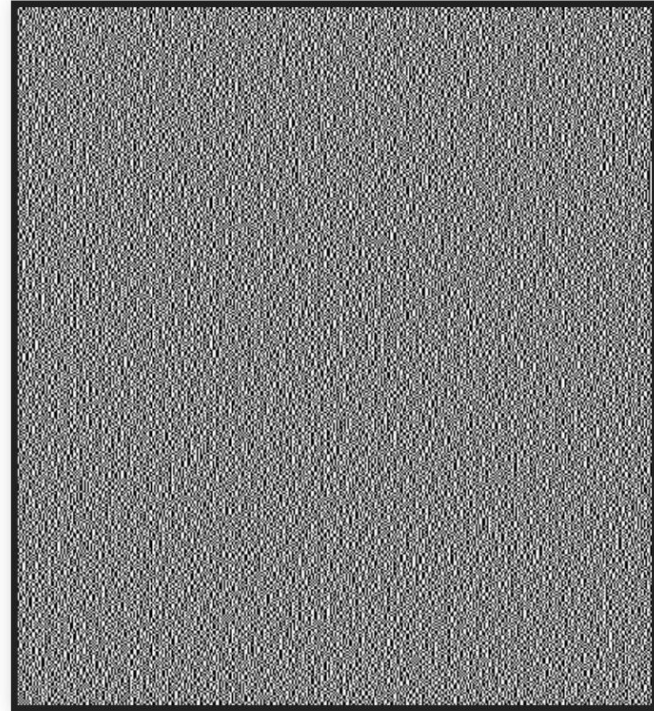
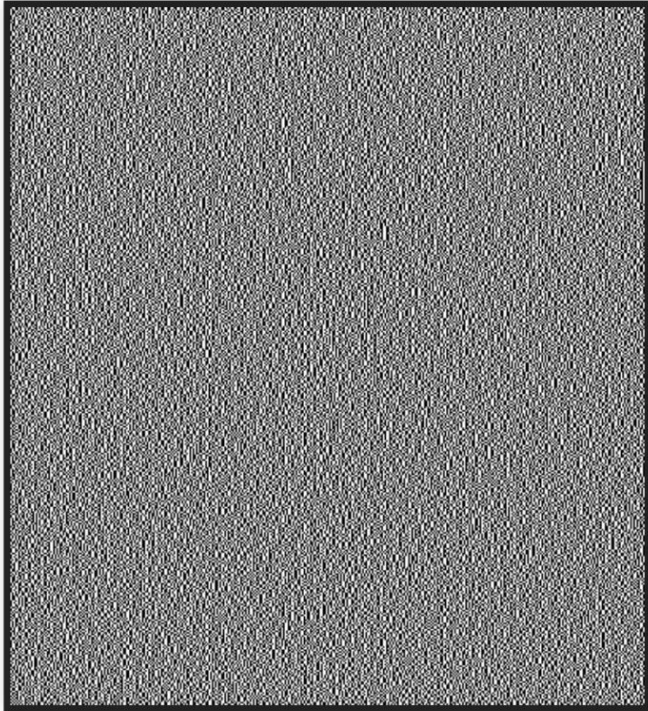
	PREDICTED 1	PREDICTED 0
TRUE 1	TP = 0	FN = 1
TRUE 0	FP = 0	TN = 9,999

accuracy ≈ 1 , **recall** = 0, **F1-score** = 0

For classifying rare events, numerical accuracy does matter!

Secure Multiparty Computation

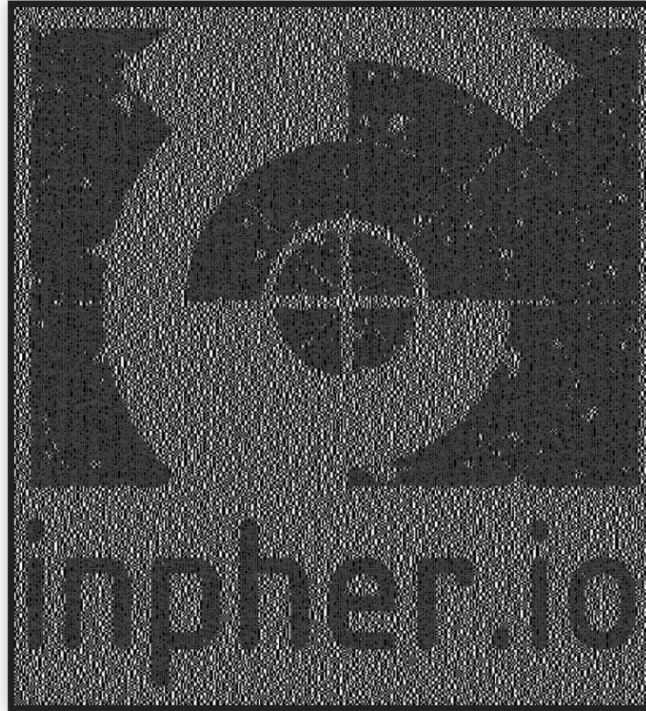
Secret Shared Data



Reveal

Secret Share

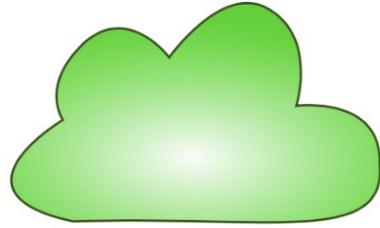
Reveal Secret Shared Data



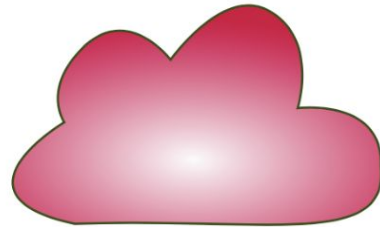
Reveal

Secret Share

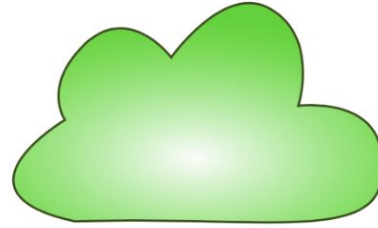
Multiplications




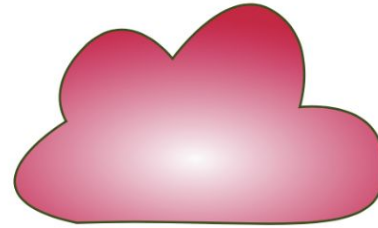
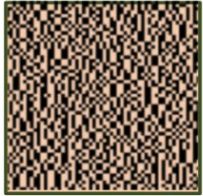
$$6 \times 7$$



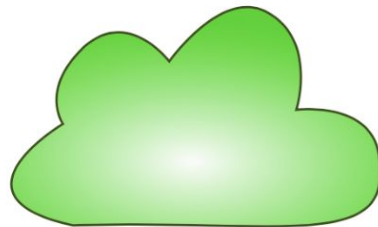
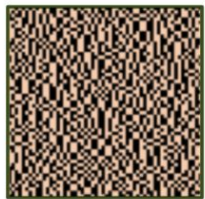
Multiplications



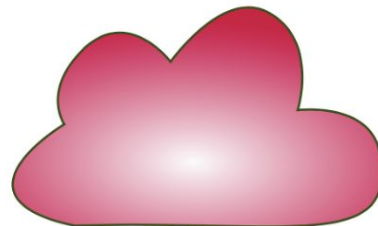
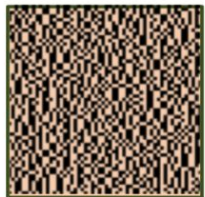
x 



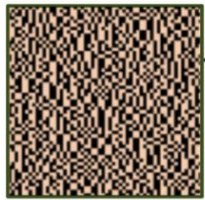
Multiplications



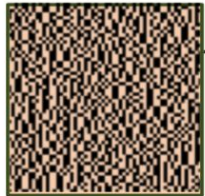
X



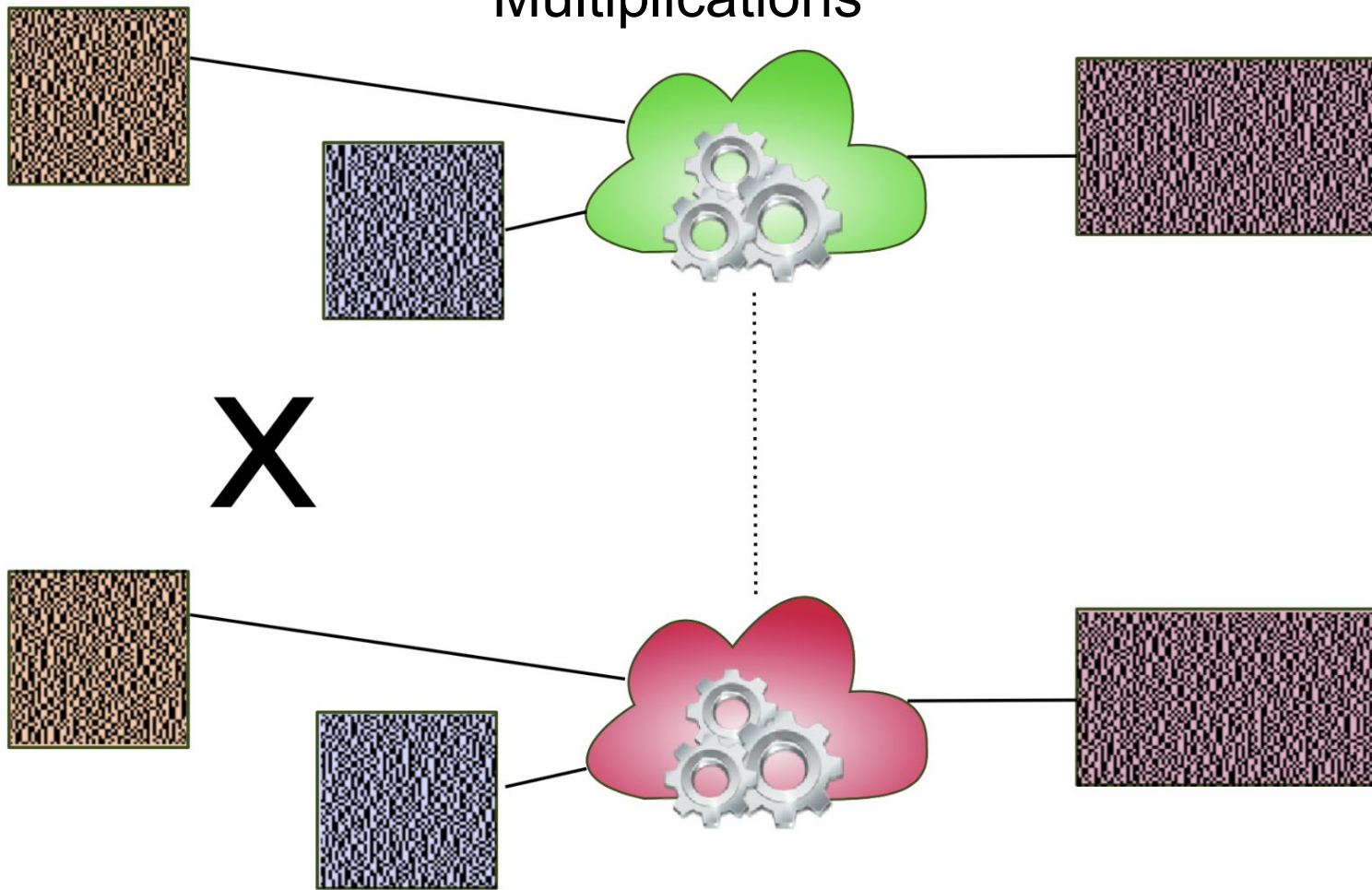
Multiplications



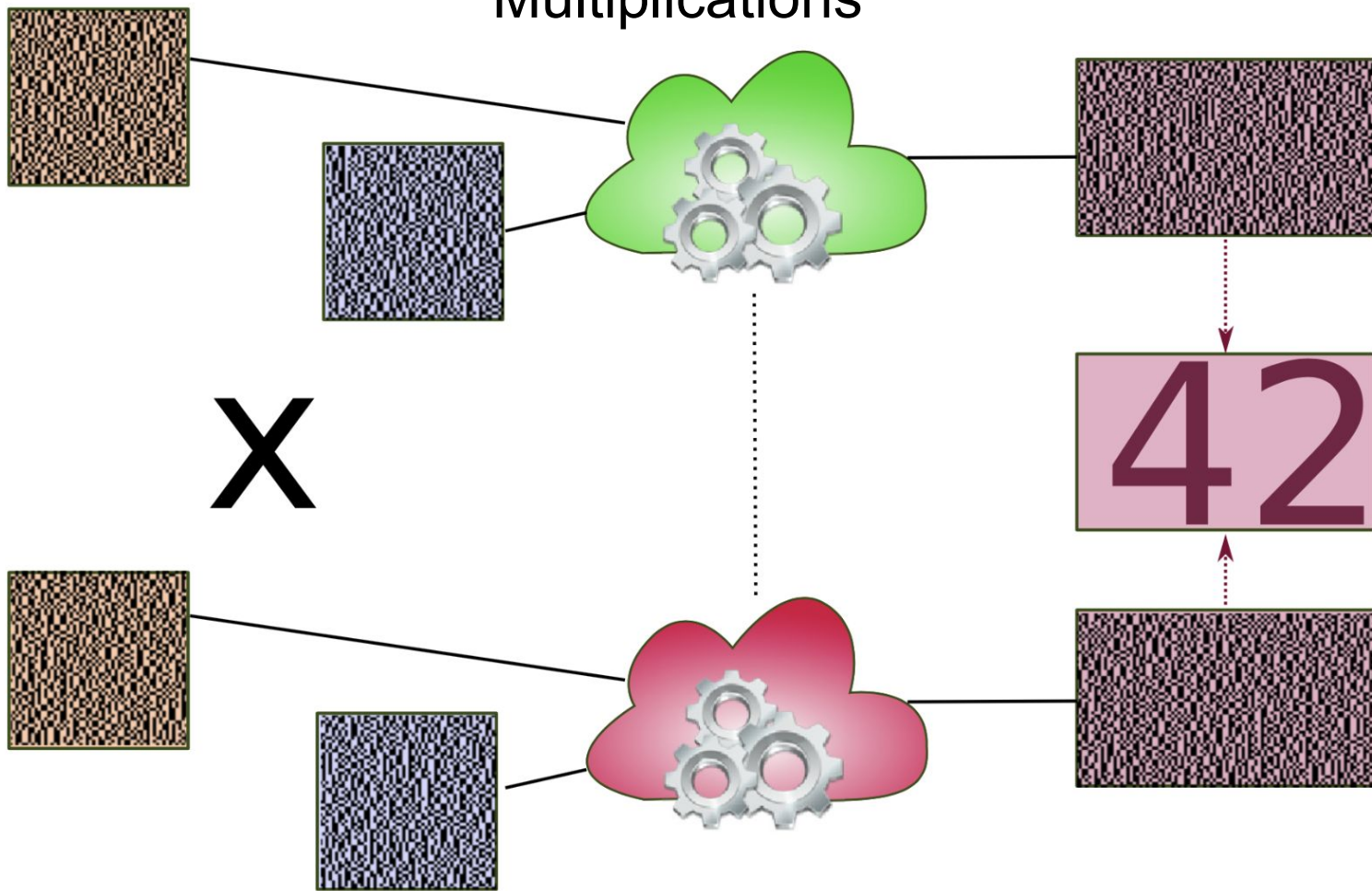
X



Multiplications



Multiplications



Beaver Multiplication

Goal

- Given $x, y \in G_1, G_2$, compute $x \times y \in G_3$
 - where $\times: G_1 \times G_2 \rightarrow G_3$ is bilinear and public

Beaver Multiplication

Goal

- Given $x, y \in G_1, G_2$, compute $x \times y \in G_3$
 - where $\times: G_1 \times G_2 \rightarrow G_3$ is bilinear and public

Offline phase (independent on the data value)

- Secret share $(\lambda, \mu, \lambda \times \mu)$ for random λ, μ

Beaver Multiplication

Goal

- Given $x, y \in G_1, G_2$, compute $x \times y \in G_3$
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Offline phase (independent on the data value)

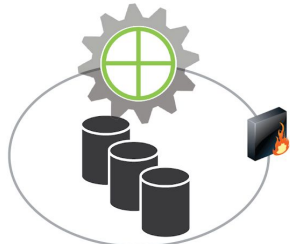
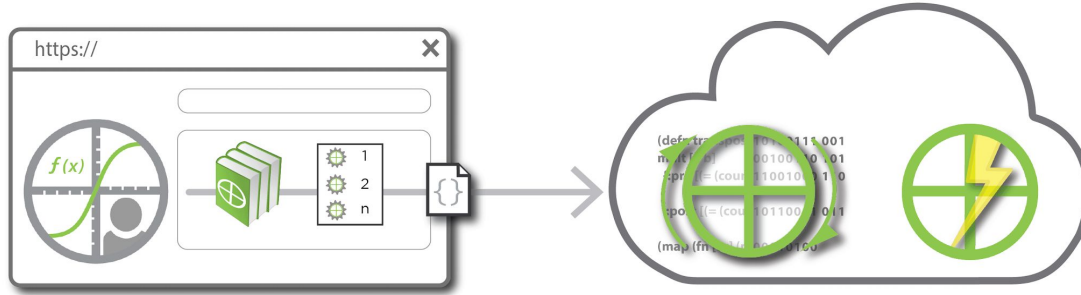
- Secret share $(\lambda, \mu, \lambda \times \mu)$ for random λ, μ

Online phase

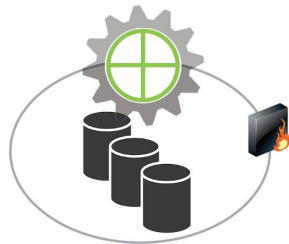
- Jointly reveal $a = x + \lambda$
- Jointly reveal $b = y + \mu$
- Now, everything becomes linear:
$$x \times y = a \times b - \lambda \times b - a \times \mu - \lambda \times \mu$$
- And **never ever re-use** the same triplet twice!

Customer-hosted Analyst Platform
(cloud or on-prem)

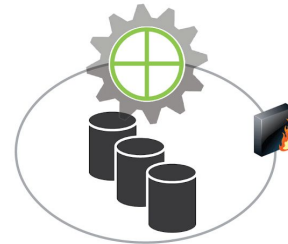
Inpher-hosted XOR Service
(never exposed to data)



Data Source 1



Data Source 2



Data Source n...

Analyst submits operations to XOR Service and selects data sources

Customer-hosted Analyst Platform
(cloud or on-prem)

Inpher-hosted XOR Service
(never exposed to data)

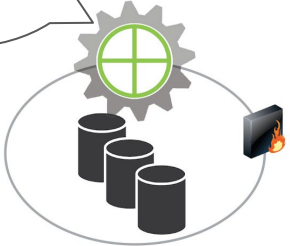


frontend
(API, UI)

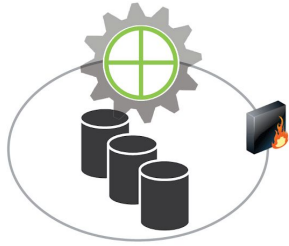
compiler

trusted dealer

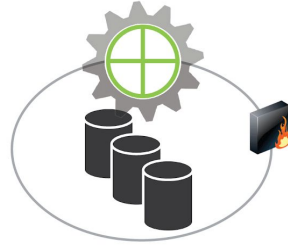
engine



Data Source 1



Data Source 2

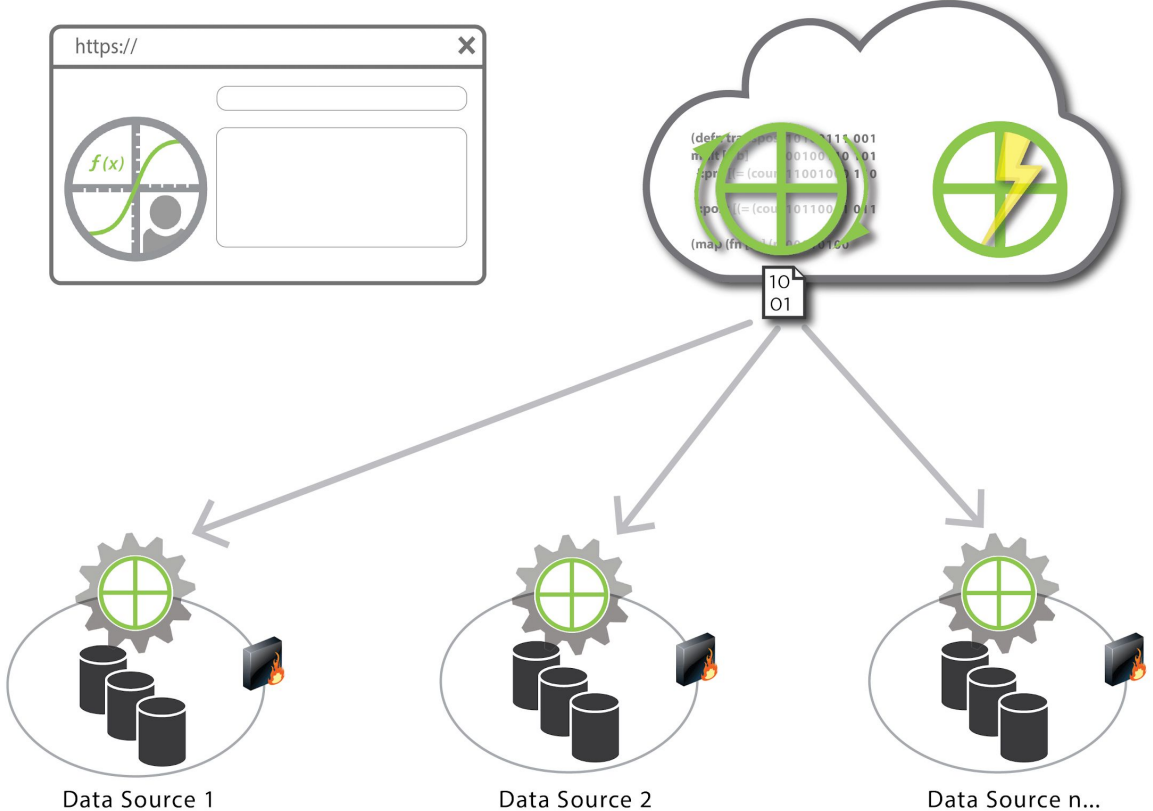


Data Source n...

Analyst submits operations to XOR Service and selects data sources

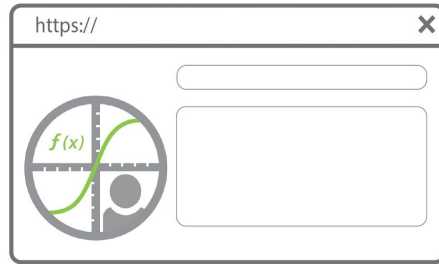
Customer-hosted Analyst Platform
(cloud or on-prem)

Inpher-hosted XOR Service
(never exposed to data)

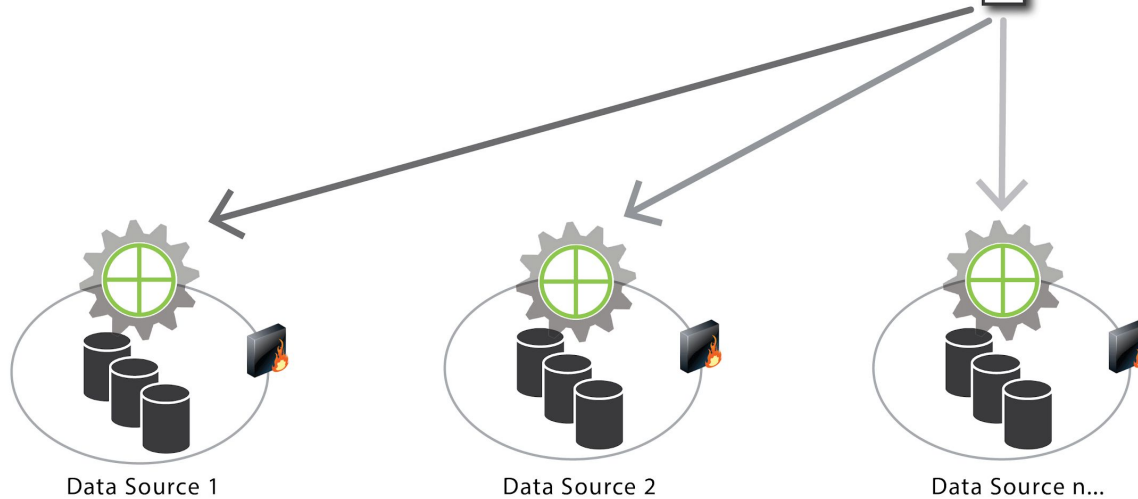
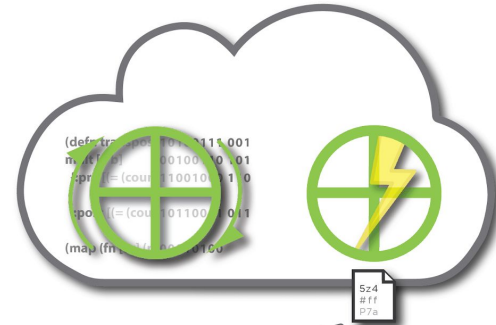


Operations compiled into a 'circuit' and distributed as a binary

Customer-hosted Analyst Platform (cloud or on-prem)

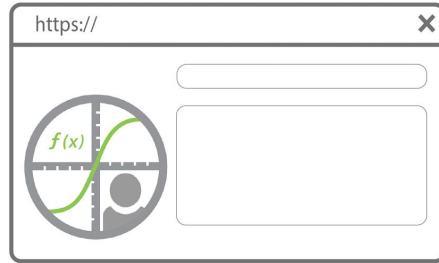


Inpher-hosted XOR Service (never exposed to data)

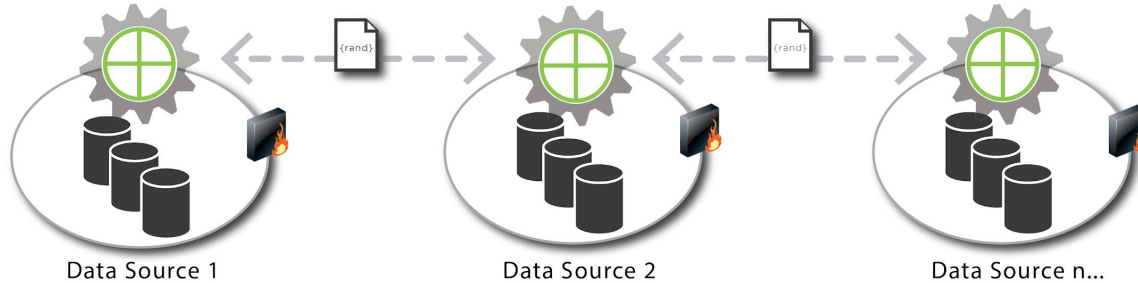


Offline Phase: Random triplets are generated and distributed

Customer-hosted Analyst Platform (cloud or on-prem)



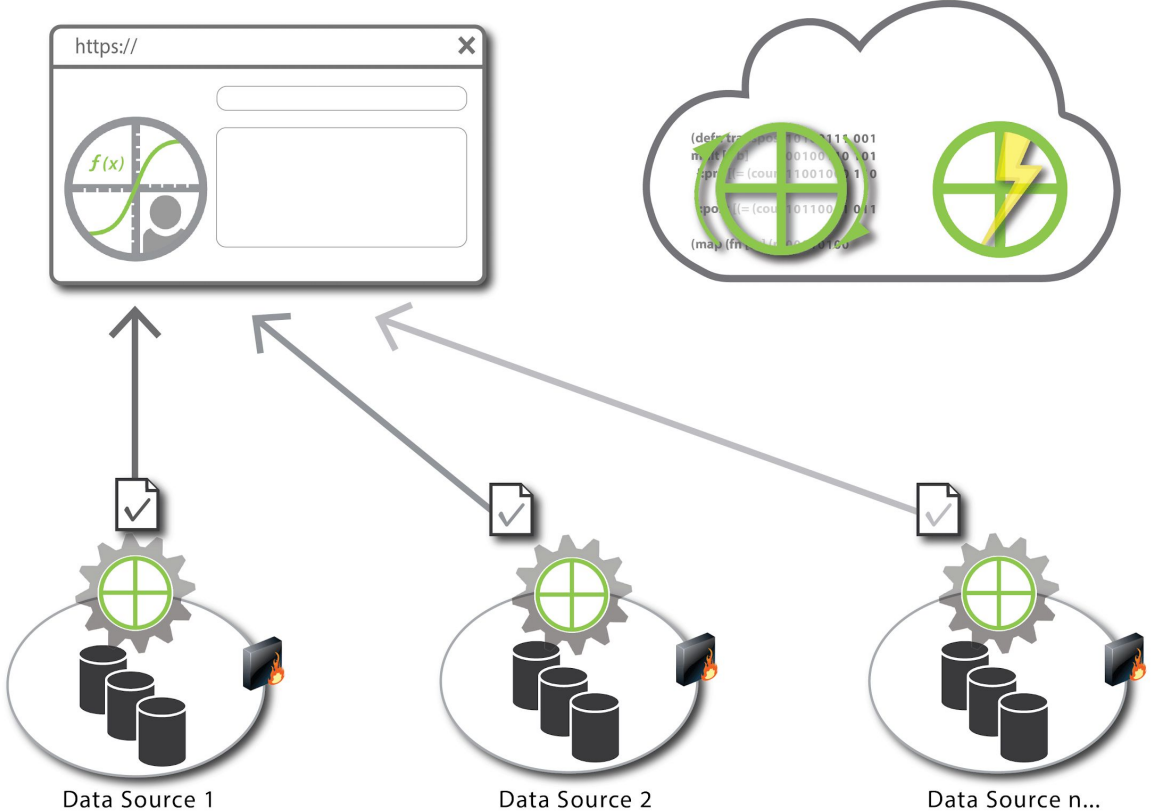
Inpher-hosted XOR Service (never exposed to data)



Online Phase: Data sources secretly compute with random numbers

Customer-hosted Analyst Platform
(cloud or on-prem)

Inpher-hosted XOR Service
(never exposed to data)



Partial results sent to Analyst Platform to construct final output

Arithmetic with Real Numbers

Computations with Real Numbers

Floating-point representation of the reals

- Addition is generally inefficient compared to multiplication
- Boolean circuit approach is slow in MPC

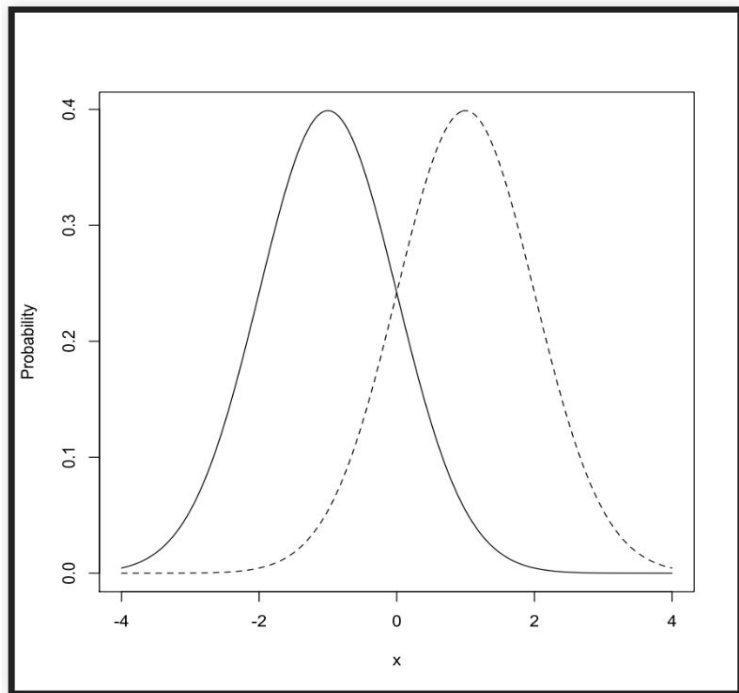
Fixed-point representation

- Overflows often blindly destroy the result

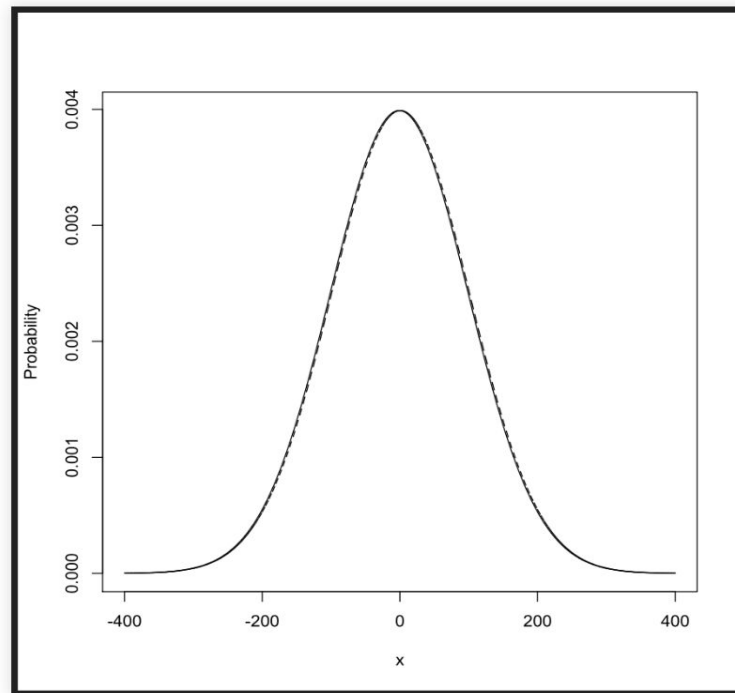
Fixed-point arithmetic with native FP backend

- Pros
 - Overflows do not destroy the result
 - **float128** addition and multiplication: native on some hardware
- Cons
 - Small impact on security
 - Statistical masking instead of perfect masking

Statistical Masking



Masking $x = \pm 1, \sigma = 1$.



Masking $x = \pm 1, \sigma = 100$.

Disadvantages of Real Arithmetic with Floating Point Backend

- Large-depth arithmetic circuits require multi-precision floating-point numbers (masking sizes grow with depth)
- **Computational security** as opposed to **information-theoretic security**
- Memory overhead in both offline and online phases.
- Matrix operations over multi-precision floating types may be expensive

Representing Real Numbers

Floating-point representation

- $x = m \cdot 2^\tau$, $m \in 2^{-\rho} \cdot \mathbb{Z}$, $1/2 \leq |m| \leq 1$
- $\tau = \lceil \log_2 |x| \rceil$ - exponent; data dependent, not MPC-friendly, not public

Fixed-point representation

- $x = m \cdot 2^\tau$ with $m \in 2^{-\rho} \cdot \mathbb{Z}$, $0 \leq |m| < 1$,
- τ is public, MPC-friendly
- Might **overflow** if τ is too small
- Might **underflow** if τ is too large

Addition is more subtle than you might think!

- Given (m_1, τ_1) and (m_2, τ_2) as well as τ
- Compute $m \cdot 2^\tau = m_1 \cdot 2^{\tau_1} + m_2 \cdot 2^{\tau_2}$ with a numerical window of size ρ
- Addition requires right-shift and roundings (non-linear operations)

Overflows and Underflows

The class of a value is known in compile/runtime, but not the value itself.

Plaintext Overflow

We know that $3 \in \mathcal{P}_{2,-2}$, but neither $3 + 3$, nor 3×3 is in $\mathcal{P}_{2,-2}$, i.e.,

- $\mathcal{P}_{\text{pmsb},\text{pls}}$ is closed neither under addition nor under multiplication.
- Compute (at compile time) a sharp upper bound pmsb for the result.

Plaintext Underflow

We know $x = 1 \times 10^{-3}, y = 6 \times 10^{-3} \in \mathcal{P}_{0,-14}$.

- If resulting class is still $\mathcal{P}_{0,-14}$, we lose the result

$$0.0010 \times 0.0060 = 0.0000$$

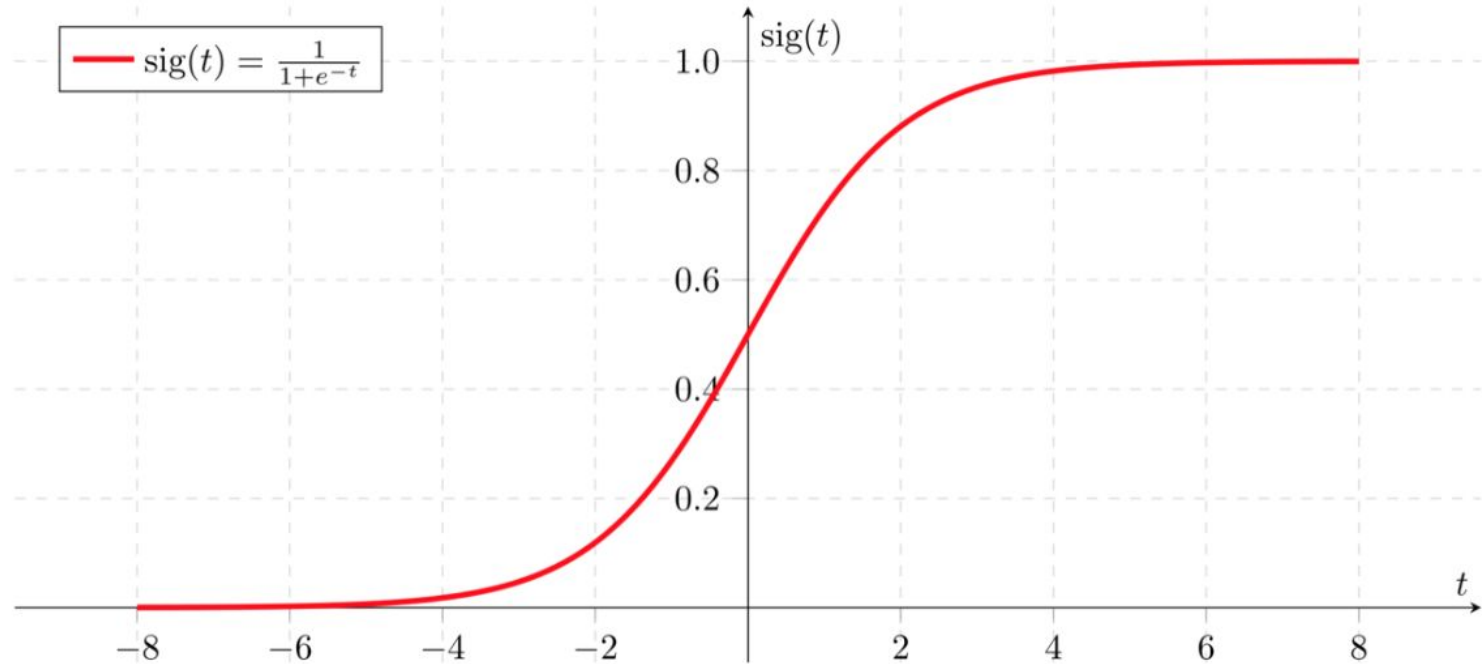
- Need for computing a suitable pls at compile time

Casting Between Classes and Arithmetic Operations

- One of the same real number can be represented with different parameters
 - mantissa, exponent, numerical window
- Need methods to cast from one representation to another
- Casts are key for implementing addition and multiplication

Fourier Approximation of Real-Valued Functions

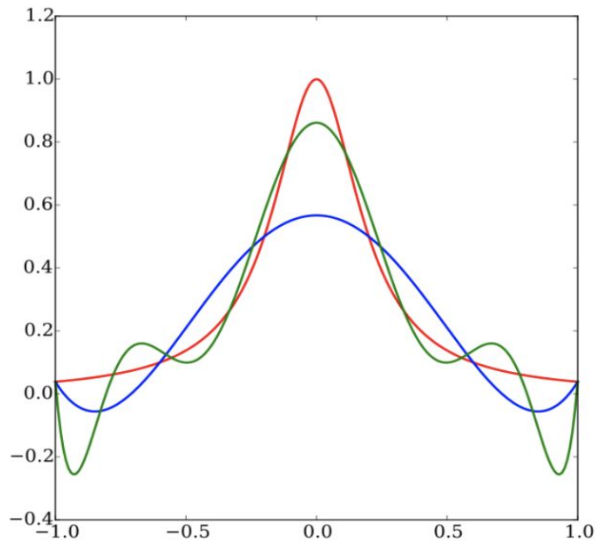
Approximation of Non-Linear Functions



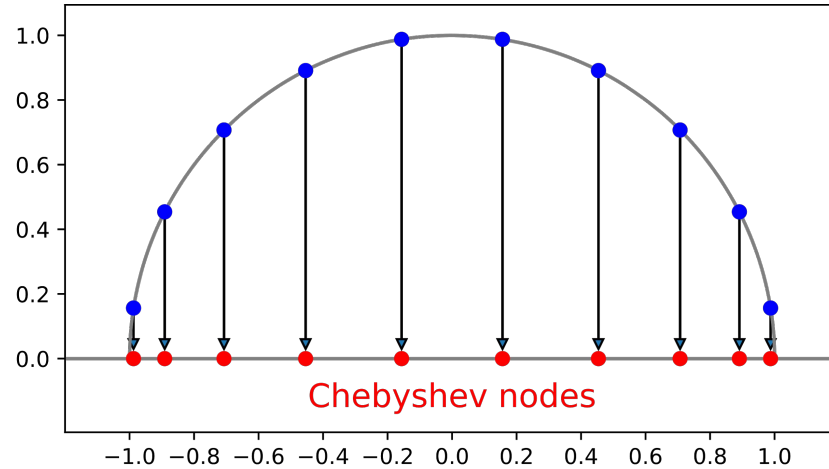
Deficiency of Polynomial Approximation

Limitations of polynomial approximation

- Evaluation requires multiple rounds
- Overflows are difficult to manage
- Approximation diverges quickly outside of the domain
- Uniform approximation fails (Runge's phenomenon)



Chebyshev Polynomials and Polynomial Approximations



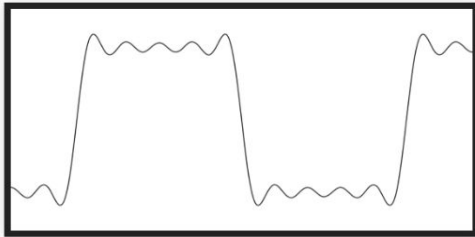
Chebyshev Polynomials

- Polynomial T_n of degree n such that $T_n(\cos \theta) = \cos n\theta$
- Optimal solution to the Runge phenomenon in degree n

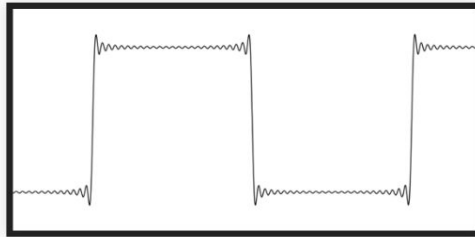
Naive Fourier Approximation

Naive approach via Fourier series

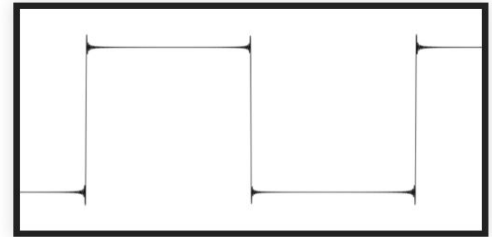
- $a_n = \frac{1}{2B} \int_{-B}^{+B} f(x) e^{\frac{\pi i n x}{B}} dx$
- Consider $f(x) = \sum_{k=-n}^n a_k e^{\frac{\pi i k x}{B}}$
- Gibbs phenomenon is an issue



$n = 5$



$n = 25$



$n = 125$

Privacy-Preserving Evaluation of Fourier Series

Fourier Triplets

- Fourier series can be evaluated in MPC

- $h(x) = \sum_{i=-n}^n a_k e^{ikx} \Rightarrow$ triplets replaced $(\lambda, e^{\pm i\lambda}, \dots, e^{\pm in\lambda})$

Periodic extensions on larger intervals

To evaluate a function f on an interval $[-B, B]$:

- Extend f to a periodic function on $[-2B, 2B]$
- Consider the Fourier series of the extension

Rapidly Convergent Uniform Approximation

$f: [-\pi/2, \pi/2) \rightarrow \mathbb{R}$ - not necessarily smooth or periodic (square-integrable)

The approximation problem

Given n , define

$$G_n = \left\{ g(x) = \frac{a_0}{2} + \sum_{k=1}^n a_k \sin kx + \sum_{k=1}^n b_k \cos kx \right\}.$$

of 2π -periodic functions. Consider

$$g_n(x) = \operatorname{argmin}_{g \in G_n} \|f - g\|_{L^2_{[-\pi/2, \pi/2)}}$$

- Coefficients with respect to the standard basis are numerically unstable (diverge as $n \rightarrow \infty$)
- Coefficients with respect to a basis of Chebyshev polynomials (first and second kind) is stable; **exponential convergence**

Building Logistic Regression Models

Requires a privacy-preserving evaluation of **sigmoid function**:

$$h_{\theta}(\mathbf{x}) = \frac{1}{1 + e^{-\theta \cdot \mathbf{x}}},$$

as well as minimization of the **cost function**:

$$J(\theta) = \frac{1}{N} \sum_{i=1}^N \text{cost}(h_{\theta}(\mathbf{x}^{(i)}), y^{(i)}),$$

where

$$\text{cost}(h_{\theta}(\mathbf{x}), y) = -y \log(h_{\theta}(\mathbf{x})) - (1 - y) \log(1 - h_{\theta}(\mathbf{x})).$$

Logistic Regression - 1M x 50 - 3 Players

	[FC2018]	Xor v2.
Abs precision	2.3e-5	1.7e-8 ✓
Offline Time	04:06:43	00:36:40
Offline RAM	276G	6.87G
Triplets pp.	51.2G	92.0G
Online (100 MBps)	03:18:19	00:24:30
Online RAM	192G	10.1G
Online Comm pp.	20G	66.8

Methods for Compiling Privacy-Preserving Programs

Why a Compiler?

AUTOMATION AND STATIC ANALYSIS

- Computation requires auxiliary random masking data (offline phase)
- Random data generated from distributions with specific parameters
- **==>** need for **static analysis of distributions (statistical calculator)** (compile time)
- Optimizations (memory/communication)

CONSTRUCTS SPECIFIC TO MPC

- Type checking, ANF, SSA (standard phases of compilation)
- Inline function definitions
- Unroll **for** loops with bounded number of iterations

Linear Regression - Source

```
def solve(A: Matrix, b: Vector): Vector {  
  var nrows: Int = xor.rows(A);  
  var ncols: Int = xor.cols(A);  
  
  var P: Matrix = xor.orthrand(nrows, ncols, -6);  
  var Q: Matrix = xor.orthrand(nrows, ncols, -6);  
  
  var PAQ: Matrix = P * A * Q;  
  var Pb: Vector = P * b;  
  
  xor.reveal(PAQ);  
  xor.reveal(Pb);  
  var r: Vector = xor.publicSolve(PAQ, Pb);  
  return Q * r;  
}
```

```
def linreg(y: Vector, X: Matrix): Vector {  
  var A: Matrix = xor.transpose(X) * X;  
  var b: Vector = xor.transpose(X) * y;  
  return solve(A, b);  
}  
  
def main() {  
  var X: Matrix = xor.input("X");  
  var y: Vector = xor.input("y");  
  var theta: Vector = linreg(y, X);  
  xor.output(theta, "thetas");  
}
```

Linear Regression - Source

```
def solve(A: Matrix, b: Vector): Vector {  
  var nrows: Int = xor.rows(A);  
  var ncols: Int = xor.cols(A);  
  
  var P: Matrix = xor.orthrand(nrows, ncols, -6);  
  var Q: Matrix = xor.orthrand(nrows, ncols, -6);  
  
  var PAQ: Matrix = P * A * Q;  
  var Pb: Vector = P * b;  
  
  xor.reveal(PAQ);  
  xor.reveal(Pb);  
  var r: Vector = xor.publicSolve(PAQ, Pb);  
  return Q * r;  
}
```

builtin

builtin

```
def linreg(y: Vector, X: Matrix): Vector {  
  var A: Matrix = xor.transpose(X) * X;  
  var b: Vector = xor.transpose(X) * y;  
  return solve(A, b);  
}
```

builtin

```
def main() {  
  var X: Matrix = xor.input("X");  
  var y: Vector = xor.input("y");  
  var theta: Vector = linreg(y, X);  
  xor.output(theta, "thetas");  
}
```

builtin

```
manojoport in ~/workspace/inpher/xor-compiler
```

```
± |master {4} U:1 ? :5 X| → xorc -L
```

Index	Phase	Brief
0	parse	Parses the program.
1	namer	Enters symbols for all top-level functions.
2	typer	Checks that the program is well typed, and performs some basic type inference.
3	anf	Transform the program in A-normal form.
4	ssa	Transforms the tree into its Static Single-Assignment (SSA) form.
5	inline	Inlines all functions called by the main function into its body.
6	tuple-elimination	Eliminates tuples creation and projections.
7	copy-propagation	Removes intermediate variables from assign-chains, and other unused variables.
8	constant-fold	Performs basic partial evaluation and folds constants through the program.
9	dimension-checking	Checks the dimensions of all matrices, and ensures that the operations are valid.
10	desugaring	Transforms a user-level program into one that operates on MPC-level primitives only.
11	visibility	Tracks and sets the visibility of all values.
12	plaintext-param	Computes plaintext parameters pMsb and pLsb.
13	mask-resolution	Resolves masking parameters from plaintext parameters.
14	builtin-params-resolution	Computes extra parameters specific to builtins.
15	codegen	Generates a compiled-program.bin that can be executed by an appropriate backend.



```
print program after given phase.
+ 0 if the program was compiled successfully
+ 1 otherwise

ENVIRONMENT
  JAVA_OPTS
    command-line options to pass to the underlying JVM

EXAMPLES
  Assume file main.xor with contents:

      def main() {
        var v1: Vector = xor.input("v1");
        var v2: Vector = xor.input("v2");
        var corr: Float = v1 * v1;
        xor.output(corr, "product");
      }

  Assume file iodb.csv with contents:

      # Placeholder name, visibility, rows, cols, msb, lsb
      v1, secret, 5, 1, 5, -2
      v2, secret, 5, 1, 5, -2

  Run the xor compiler with the following invocation:

      xorc --iodb iodb.csv main.xor -o main.xbin

  This will produce a compiled program in main.xbin.

AUTHORS
  Inpher, Inc.
```

```
Manual page (stdin) line 1/104 62% (press h for help or q to quit)
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Manual page (stdin) line 47/104 (END) (press h for help or q to quit)
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June 2019

XORC(1)

Linear Regression - Assembly

```
: ...
6: CreateContainer(V6, FLMR<2,2,9,7,-43>);
7: BeaverMod(PriV1, PriV1, V6, AW=(29,-20), BW=(29,-20), W=(9,-40), Pairing=4);
8: CreateContainer(V8, FLMR<2,1,15,13,-37>);
9: BeaverMod(PriV1, PriV3, V8, AW=(35,-20), BW=(35,-20), W=(15,-40), Pairing=4);
10: {
11:     CreateContainer(V11, FLMR<2,2,2,0,-6>);
12:     RandomOrthogonalMatrix(V11);
13:     CreateContainer(V13, FLMR<2,2,2,0,-6>);
14:     RandomOrthogonalMatrix(V13);
15:     CreateContainer(V15, FLMR<2,2,14,12,-38>);
16:     BeaverMod(PriV11, PriV6, V15, AW=(52,-6), BW=(20,-38), W=(14,-44), Pairing=3);
17:     CreateContainer(V17, FLMR<2,2,15,13,-37>);
18:     BeaverMod(PriV15, PriV13, V17, AW=(21,-37), BW=(52,-6), W=(15,-43), Pairing=3);
19:     CreateContainer(V19, FLMR<2,1,16,14,-36>);
20:     BeaverMod(PriV11, PriV8, V19, AW=(52,-6), BW=(22,-36), W=(16,-42), Pairing=3);
21:     Reveal(V17);
22:     Reveal(V19);
23:     CreateContainer(V23, FLMR<2,1,26,24,-26>);
24:     PublicSolve(V17, V19, V23);
25:     CreateContainer(V25, FLMR<2,1,27,25,-25>);
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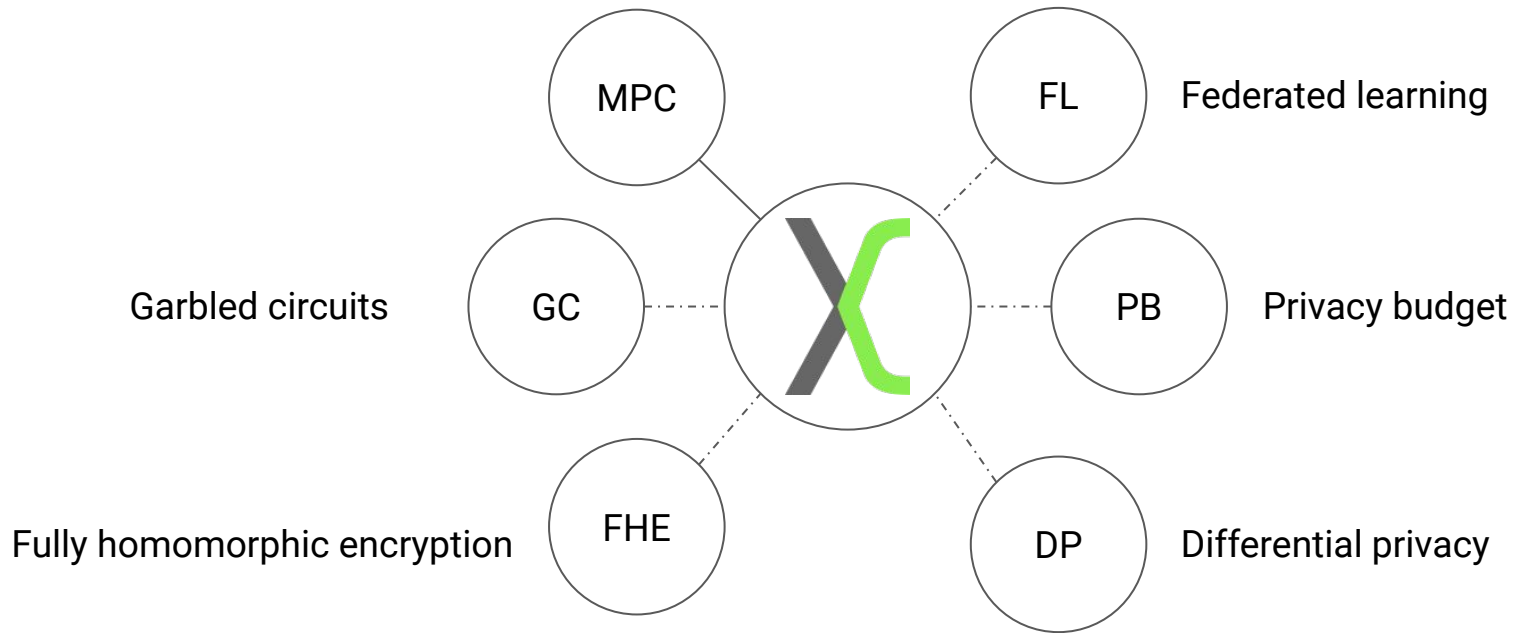
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Compiling to Preserve Privacy - Beyond MPC



Other Applications - Compiling FHE Programs

Bootstrapping: an operation used to reduce noise in the plaintext in order to continue processing the ciphertext in a computation

Ring-LWE-based FHE Schemes

- TFHE - suitable for boolean circuits, automata evaluations
- B/FV - suitable for integer arithmetic, arithmetic circuits
- HEAAN - suitable for vectorized operations with real numbers
- CHIMERA - scheme switching method

Numerical Parameters in the Context of FHE

- L - level exponent of ciphertext - related to the maximal number of homomorphic operations before performing a **bootstrapping**
- ρ - numerical window (as in the MPC setting)
- τ - exponent (only know a sufficiently good bound at compile time)

Thank you!