

# Homomorphic Encryption

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# Why Homomorphic Encryption?

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Consumers are increasingly concerned about **data privacy**

How can businesses leverage on big data while being cautious of data privacy?



# Why Homomorphic Encryption?

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**Homomorphic Encryption** is a  
*Privacy-Enhancing Technology* that can  
achieve Data Privacy

# History of Homomorphic Encryption

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- Rather new technology; 30+ years since developed
- **Limited commercial applications** due to lack of specialist knowledge and standardisations
- In recent years, tech leaders (IBM, Google, Microsoft) are pushing for their widespread use

# Homomorphic Encryption (HE)

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- Based on Homomorphisms, a special type of mathematical function
- Fundamentally different from current encryption systems like RSA or AES
- **Quantum-resistant:** RSA is vulnerable in a post-quantum world, but Homomorphic Encryption is not

# Homomorphisms

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$$\text{Enc}(a) + \text{Enc}(b) = \text{Enc}(a + b)$$

*“property-preserving” function*

# Homomorphisms

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$$\text{Enc}(a) + \text{Enc}(b) = \text{Enc}(a + b)$$

Adding encrypted messages

Adding unencrypted messages

*“property-preserving” function*

# Homomorphic Encryption (HE)

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- Property-preserving encryption
- **Able to run algorithms on encrypted data**
- Results will be as if the algorithms were run on the raw, unencrypted data




## A Common Scenario

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- Client Company A: owns the raw data
  - Server Company B: owns the software/ analytics ability
- Both parties are unwilling to share with each other

## Solution: Homomorphic Encryption

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1. Client encrypts raw data
  2. Client sends encrypted data to server
  3. Server **computes on encrypted data**
  4. Server returns encrypted results to client
  5. Client decrypts results
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- Data is encrypted for the server

*Result is as if server performed computations on raw data*

# Pros & Cons of HE

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Benefits	Disadvantages
Allows computations on encrypted data	<b>Significantly slower</b> than non-homomorphic encryption
<b>Resolves the data privacy conflict</b> between data owners and analytics companies	Lack of readily-available toolkits and standardisations (still in development!)
	Inherently not CCA-secure, which limits its applications

# Key Applications of HE

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## **Healthcare analytics**

- Companies and governments holding sensitive data can outsource the analytics

## **Encrypted search**

- Search can be done by only indexing encrypted data

## **End-to-end verifiability in voting systems**

- Elections can be audited without revealing votes

# Security Problems of Homomorphic Encryption

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## HE is not CCA secure

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Adding any two ciphertexts A and B together will result in a **valid ciphertext** C. This property-preserving function of HE is known as ciphertext **malleability**.

Given the ciphertexts of A, B and C, attackers can discover that  $C = A + B$ . **Attackers know the relationship between the ciphertexts.**

## HE is not CCA secure

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Actual value of  $C$  is protected since actual values of  $A$  and  $B$  are not known.

However, what if the attacker can know  $A$  and  $B$ ?

Then, the security of the HE scheme is compromised.

## HE is not CCA secure

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Data owners need to ensure that the raw data cannot be easily accessible.

However, applications can be very complex and include multi-party communication. **Rich data flows could lead to inadvertent data leaks.**

HE is still safe for pure outsourcing (one client one server) scenarios.



## HE is not CCA secure

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Secondly, HE does not provide integrity checks.

The attacker can simply double every data point using homomorphic operations, changing the entire database.

Currently, the only solution is to use canaries to detect these modifications.

# Developing applications using Homomorphic Encryption

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## Types of HE

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- HE is a broad class of encryption systems
- **Partially HE:** Some systems are only homomorphic for **addition only or multiplication only**, but not both
- **Somewhat HE:** Some systems only support a **limited number of operations**
- **Fully HE:** The most theoretically correct but also not practical to use

# Common HE schemes

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DGHV, BGV, BFV, CKKS (named after the researchers who developed them)

Decide on a scheme based on the data type and operations needed

- E.g. CKKS is an approximated-scheme that supports decimal operations

## Brakerski/Fan-Vercauteren (BFV)

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One of the more commonly-implemented HE schemes.

Based on the **Ring Learning with Error (RLWE)** problem that is computationally hard to solve.

Supports both public-key and symmetric encryption.

# BFV

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Encryption adds **noise** to the messages

- Without the key, it is difficult to decrypt the noisy messages

**Noise grows during computation process**

- Adding two ciphertexts: negligible growth
- Multiplying two ciphertexts: noise almost doubles

# BFV

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Once noise exceeds threshold, it is not possible to decrypt the message correctly

Able to “**reset**” the noise by **bootstrapping**

- Decrypt and re-encrypt the messages
- Very expensive operation (HE is slow)

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Name	Date modified	Type	Size
demo1-8192.exe	6/7/2020 4:33 pm	Application	1,783 KB
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demo1x.exe	23/6/2020 6:10 pm	Application	1,783 KB
demo2.exe	23/6/2020 5:49 pm	Application	1,783 KB
demo3-client.exe	6/7/2020 4:15 pm	Application	1,731 KB
demo3-server.exe	6/7/2020 4:15 pm	Application	1,783 KB
Homomorphic Encryption.pptx	6/7/2020 12:44 pm	Microsoft PowerPoint...	212,817 KB
Homomorphic Encryption_FULL_VIDEOS.pptx	6/7/2020 11:49 am	Microsoft PowerPoint...	212,825 KB

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```

C:\Users\Joyce\Desktop\presentation\demo1-8192.exe
Microsoft SEAL version: 3.5.3

+-----+
| Demo 1: Noise growth in BFV encryption |
+-----+

/
Encryption parameters :
  scheme: BFV
  poly_modulus_degree: 8192
  coeff_modulus size: 218 (43 + 43 + 44 + 44 + 44) bits
  plain_modulus: 2048
\

Parameter validation (success): valid

~~~~~ Calculate (x^4+1) for x = 6 ~~~~~
STEP 1 -->
Express x = 6 as a hexadecimal plaintext polynomial 0x6.
STEP 2 -->
Encrypt the plaintext.
  + number of polynomials (size) of freshly encrypted x: 2
  + noise budget in freshly encrypted x: 155 bits
STEP 3 -->
First, compute x_square (x^2).
  + number of polynomials (size) of x_square: 3
  + noise budget in x_square: 132 bits
STEP 4 -->
Then, compute x_fourth (x^4).
  + number of polynomials (size) of x_fourth: 5
  + noise budget in x_fourth: 101 bits
  + multiplication roughly doubles the size of the ciphertext
STEP 5 -->
Next, add 1 to the result (x^4 + 1).
  + number of polynomials (size) of x_fourth_plus_one: 5
  + noise budget in x_fourth_plus_one: 101 bits
  + addition is a negligible operation and does not have a large effect on the noise
STEP 6 -->
  + decryption of encrypted_result: 0x511 ..... expected was 0x511

~~~~~ End of Program ~~~~~

```

## demo1: Summary of Steps

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1. Encrypt plaintext  $x$  to get  $\text{Enc}(x)$
2.  $\text{Enc}(x^2) = \text{Enc}(x) * \text{Enc}(x)$
3.  $\text{Enc}(x^4) = \text{Enc}(x^2) * \text{Enc}(x^2)$
4.  $\text{Enc}(x^4 + 1) = \text{Enc}(x^4) + \text{Enc}(1)$
5. Get a ciphertext representing  $\text{Enc}(x^4 + 1)$
6. Decrypt the ciphertext to get  $x^4 + 1$

## demo1: Summary of Steps

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1. Encrypt plaintext  $x$  to get  $\text{Enc}(x)$

$$2. \text{Enc}(x^2) = \text{Enc}(x) * \text{Enc}(x)$$

$$3. \text{Enc}(x^4) = \text{Enc}(x^2) * \text{Enc}(x^2)$$

$$4. \text{Enc}(x^4 + 1) = \text{Enc}(x^4) + \text{Enc}(1)$$

**Homomorphic  
operations**

5. Get a ciphertext representing  $\text{Enc}(x^4 + 1)$

6. Decrypt the ciphertext to get  $x^4 + 1$

## demo1: Size and noise budget changes

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Ciphertext	Size (number of polynomials)	Noise budget (Remaining noise space)
$x$	2	54
$x^2$	3	31
$x^4$	5	2
$x^4 + 1$	5	2

## demo: client-server model

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Client encrypts raw data, and holds encryption key

Server does not have access to raw data and encryption keys

C:\Users\Joyce\Desktop\presentation\demo3-server.exe

Microsoft SEAL version: 3.5.3

```
+-----+  
| Analytics Service: Server |  
+-----+
```

C:\Users\Joyce\Desktop\presentation\demo3-client.exe

Microsoft SEAL version: 3.5.3

```
+-----+  
| Analytics Service: Client |  
+-----+
```

```
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| Encryption parameters :
|   scheme: BFV
|   poly_modulus_degree: 4096
|   coeff_modulus size: 109 (36 + 36 + 37) bits
|   plain_modulus: 1024
\
```

Parameter validation (success): valid

Enter plaintext to be squared:

Type here to search



5:51 pm  
6/7/2020

```
C:\Users\Joyce\Desktop\presentation\demo3-server.exe
Microsoft SEAL version: 3.5.3
+-----+
| Analytics Service: Server |
+-----+
Size of ciphertext received: 91303 bytes
Parameter validation (success): valid

Compute x_square
Sending results back...
Size of ciphertext sent: 136594 bytes
Connection closing...
~~~~~ End of Program ~~~~~

C:\Users\Joyce\Desktop\presentation\demo3-client.exe
Microsoft SEAL version: 3.5.3
+-----+
| Analytics Service: Client |
+-----+
/
Encryption parameters :
| scheme: BFV
| poly_modulus_degree: 4096
| coeff_modulus size: 109 (36 + 36 + 37) bits
| plain_modulus: 1024
\
Parameter validation (success): valid

Enter plaintext to be squared:
4
Size of ciphertext sent: 91303 bytes
Size of ciphertext received: 136594 bytes
Connection closed
Expected result (decimal): 16
Received result (hexadecimal): 0x10
~~~~~ End of Program ~~~~~
```

## demo: Space consumption of data

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- Large increase in space consumption
- Unencrypted integers = 4 bytes
- After encryption, 100 000 bytes
- Not very scalable for large data sets



# Problems with SEAL::BFV

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Limited practical use

- **Lack of functionality - Only primitive operations are available** (addition, multiplication)
- Encryption and decryption takes up data owner's resources

Trade-off between spending resources on encryption vs spending resources on computation and analytics

# Problems with SEAL::BFV

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A rather **low-level library working with polynomial operations**

- Developers need to have an understanding of how to represent the data in polynomials
- To select the BFV parameters, there is a need to estimate the computations results beforehand
- Difficult to adapt existing machine learning models to HE libraries

# Moving Forward with HE

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Still a research-level technique.

Have to solve fundamental issues like **making basic operations faster**.

Ultimately, the goal is to create **data-agnostic software** with generic analytics capabilities.

# More about the Development Environment

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Done using native C++ on Windows

SEAL library with BFV encryption

- Homomorphic for addition and multiplication

Server is on only localhost, and communicates with Client via WinSock

# For Developers

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## Libraries:

- PALISADE (a collaboration by various universities)
- **SEAL** (Microsoft)
- HELib (IBM)
- Private Join and Compute (Google)

# Thank You!

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