

# Cryptography as a Tool against White-Box Time-Bounded Adversaries

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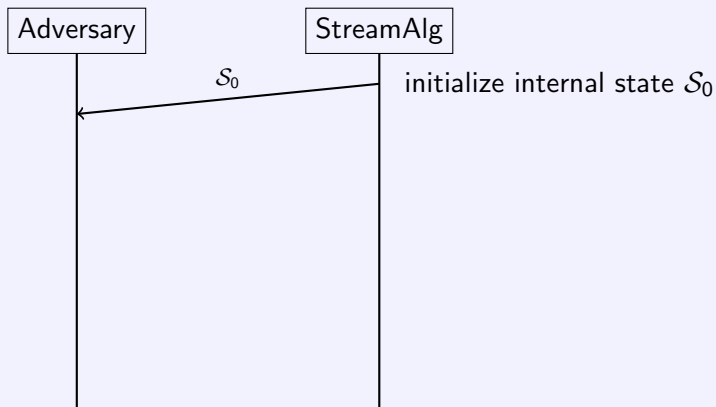
# White-Box Adversarial Streaming Model

- The dataset is chosen adaptively by an adversary who sees the internal state of the algorithm
- Motivation: It captures richer adversarial scenarios such as
  - **Dynamic algorithms:** Maintain a dynamic data structure that correctly answers queries across sequentially arrived updates  
Dynamic model often considers an adaptive adversary that sees the entire data structure
  - **Machine learning:** Design robust models  
Many successful adversarial attacks use knowledge of internal algorithmic parameters and training weights

# White-Box Adversarial Streaming Model

## Definition

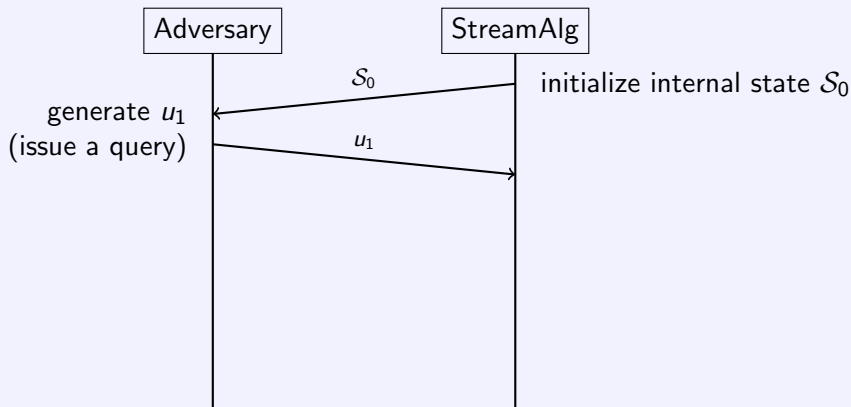
Two-player game between **StreamAlg** and **Adversary**:



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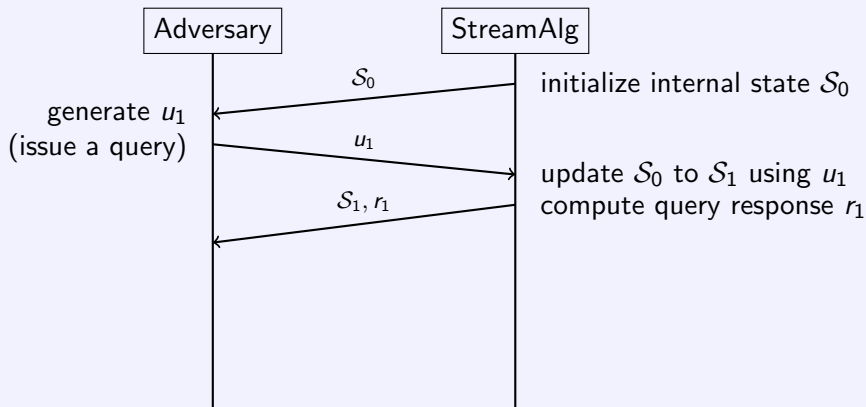
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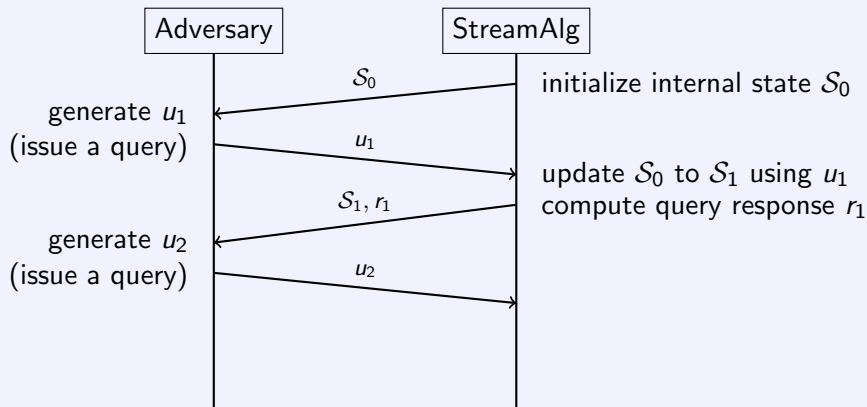
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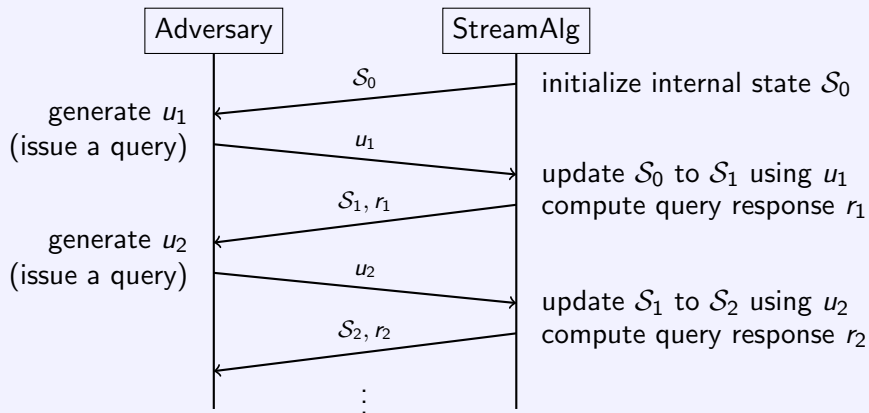
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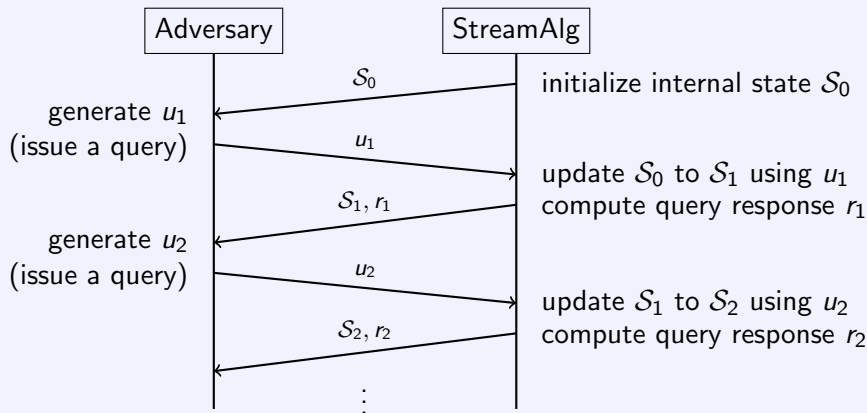
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# White-Box Adversarial Streaming Model

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Two-player game between **StreamAlg** and **Adversary**:



Adversary wins if  $r_t$  is incorrect at some time  $t$



## k-Sparse Recovery

Given an input vector  $x$ , if  $x$  contains at most  $k$  non-zero entries, recover  $x$ . Otherwise, report *invalid input*.

- Extensions to low-rank matrix and tensor recovery, Robust PCA,  $L_0$  norm estimation

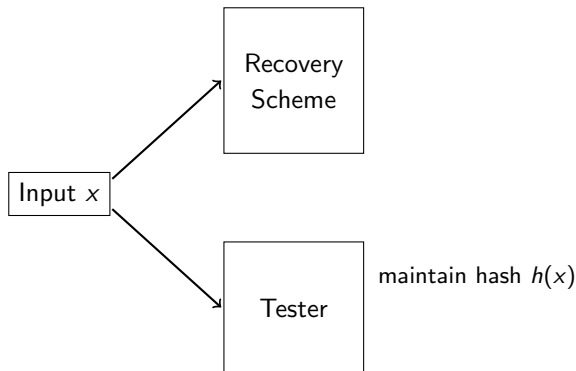
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- Space lower bound of detecting  $k$ -sparsity, against white-box unbounded adversary:  $\Omega(n)$ .
  - consider time-bounded adversaries

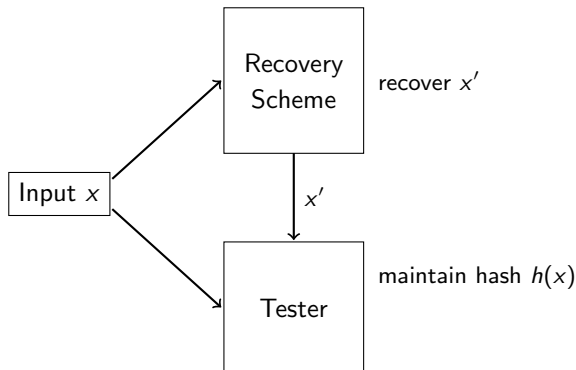
# General Framework

- Existing deterministic  $k$ -sparse recovery scheme, plus
  - assumes that the input vector  $x$  is  $k$ -sparse, and only under this promise, recovers the  $k$ -sparse  $x$
- A secure **tester** that verifies whether the input and the recovery output matches



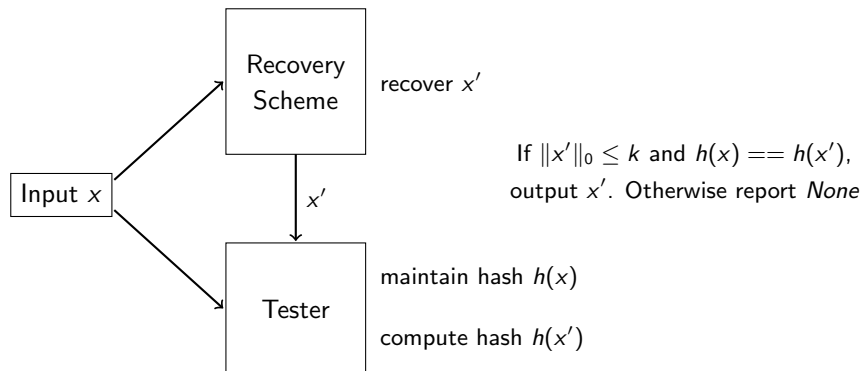
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- Tester  $\approx$  *Streaming Friendly Collision-Resistant Hash Functions*, satisfying:
  - Small-sized hash key
  - Updatable
  - White-box adversarially robust
  - Time and space efficient
- The same framework also works for low-rank matrix and tensor recovery and RPCA, by changing the deterministic recovery scheme

# Using Short Integer Solution Problem

## Definition (SIS)

Given a uniformly random matrix  $A \in \mathbb{Z}_q^{r \times n}$ , find a nonzero integer vector  $x \in \mathbb{Z}^n$  such that  $Ax = 0 \pmod{q}$  and  $\|x\|_\infty \leq \beta$ .

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Assuming subexponential hardness of SIS and  $r \geq \tilde{O}(k)$ :  
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- Otherwise adversary can brute-force all  $k$ -sparse vectors to find  $x'$
- $x - x'$  is a SIS solution
- Robust against subexp-time adversary

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Efficient reduction:

## Claim

If  $x'$  is **outputted by a polytime recovery algorithm** and  $Ax = Ax'$ , then  $x' = x$

- Standard collision-resistance
- Robust against polytime adversary

# Using Fully Homomorphic Encryption

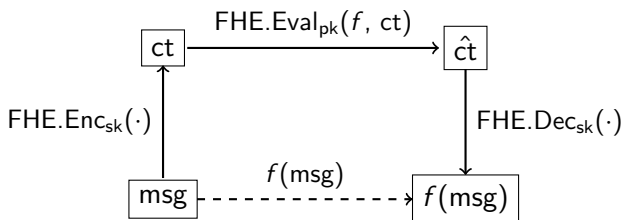
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## Definition (FHE)

An encryption scheme that enables function evaluation on **ciphertexts**, while yielding a ciphertext that encrypts the result as if the function was evaluated on plaintexts



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Can be generated on the fly
  - $f_i(msg) = \begin{cases} 1 & \text{if } msg == i \\ 0 & \text{otherwise} \end{cases}$
- Hash  $h(x)$  is the matrix-vector product
  - what is this linear combination of ciphertexts?

# FHE with Additional Properties

What is this linear combination of ciphertexts?

## Additional Property 1. (Linear Homomorphism)

If  $\hat{c}_i$  encrypts a bit  $b \in \{0, 1\}$  and  $x_i$  is a small-normed integer, then there is a decryption algorithm that uniquely decodes  $\sum_{i \in [n]} \hat{c}_i x_i$  to  $\sum_{i \in [n]} b_i x_i$

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  - if msg is hidden from the adversary:  $\Pr[x_{\text{msg}} \neq x'_{\text{msg}}] \geq \Pr[x \neq x']/n$

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The distribution of public keys and ciphertexts are indistinguishable, respectively, from some **truly random distributions** from the perspective of the adversary.

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The distribution of public keys and ciphertexts are indistinguishable, respectively, from some **truly random distributions** from the perspective of the adversary.

- Satisfied by most known FHE schemes
- Allow us to sample truly random seeds  $\tilde{ct}_1, \tilde{ct}_2, \dots, \tilde{ct}_{\log n}$  for the streaming algorithm
  - We switch to real ciphertexts  $ct_1, ct_2, \dots, ct_{\log n}$  that encrypt msg only in the security proof
  - We can derive collision-resistant hash function using these random seeds, in the same way as using real ciphertexts

Using the FHE scheme in [GSW], which is based on the hardness of the Learning-with-Error (LWE) problem:

- Assuming sub-exponential hardness of LWE, our construction takes  $\text{poly log}(n)$  space and update time<sup>a</sup> in the stream.
- Assuming polynomial hardness of LWE, our construction takes  $n^c \cdot \text{poly log}(n)$  space and update time, for an arbitrarily small constant  $c > 0$ .

---

<sup>a</sup>plus the space and time taken by the deterministic recovery scheme

# White-Box Adversarial Distributed Model

We also consider a related distributed model:

- A message-passing coordinator model with  $t$  servers and one central coordinator
- Each server receives a white-box adversarially generated data vector  $x_i$  and communicates with the coordinator
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Use a strong definition of white-box adversary:

- Before the communication starts, the adversary observes the complete random string that is going to be used by all parties
- It then generates data for each server

# Results

We can adapt our streaming algorithm to construct a communication protocol for the distributed model. Using the LWE-based FHE in [GSW]:

- Bits of communication  $\approx$  space of streaming algorithm
- Process time  $\approx n \cdot$  stream update time

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- By packing partitioned segments of the input vector as ring elements
- Efficiently operations on ring elements using FFT