IEEE ICC®

GRAND-EDGE: A Universal, Jamming-resilient Algorithm with Error-and-Erasure Decoding

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Communicating over Adversarial Conditions

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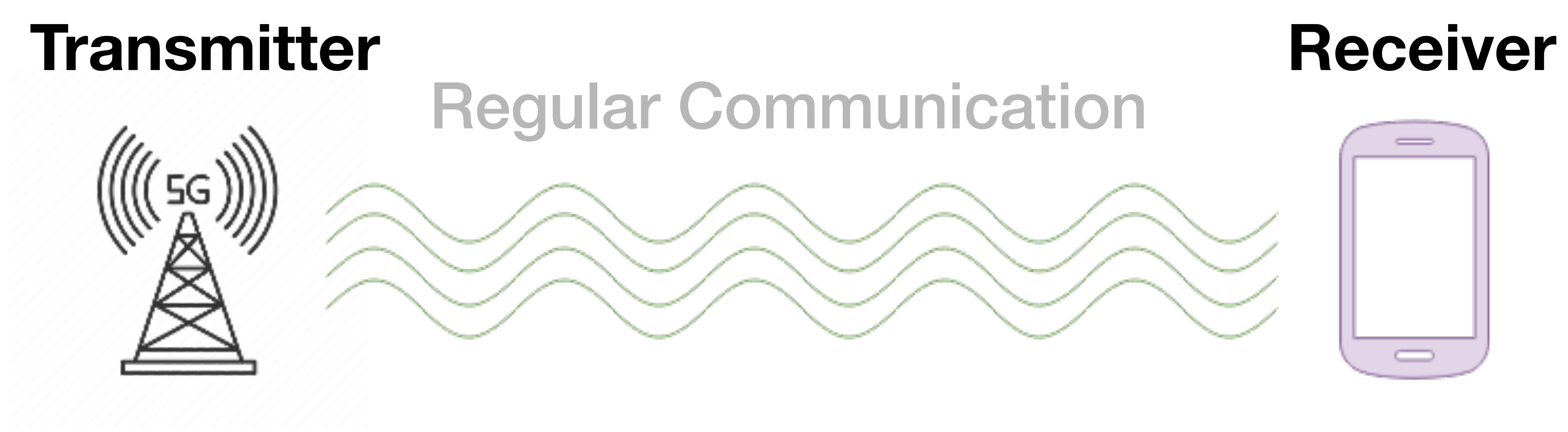
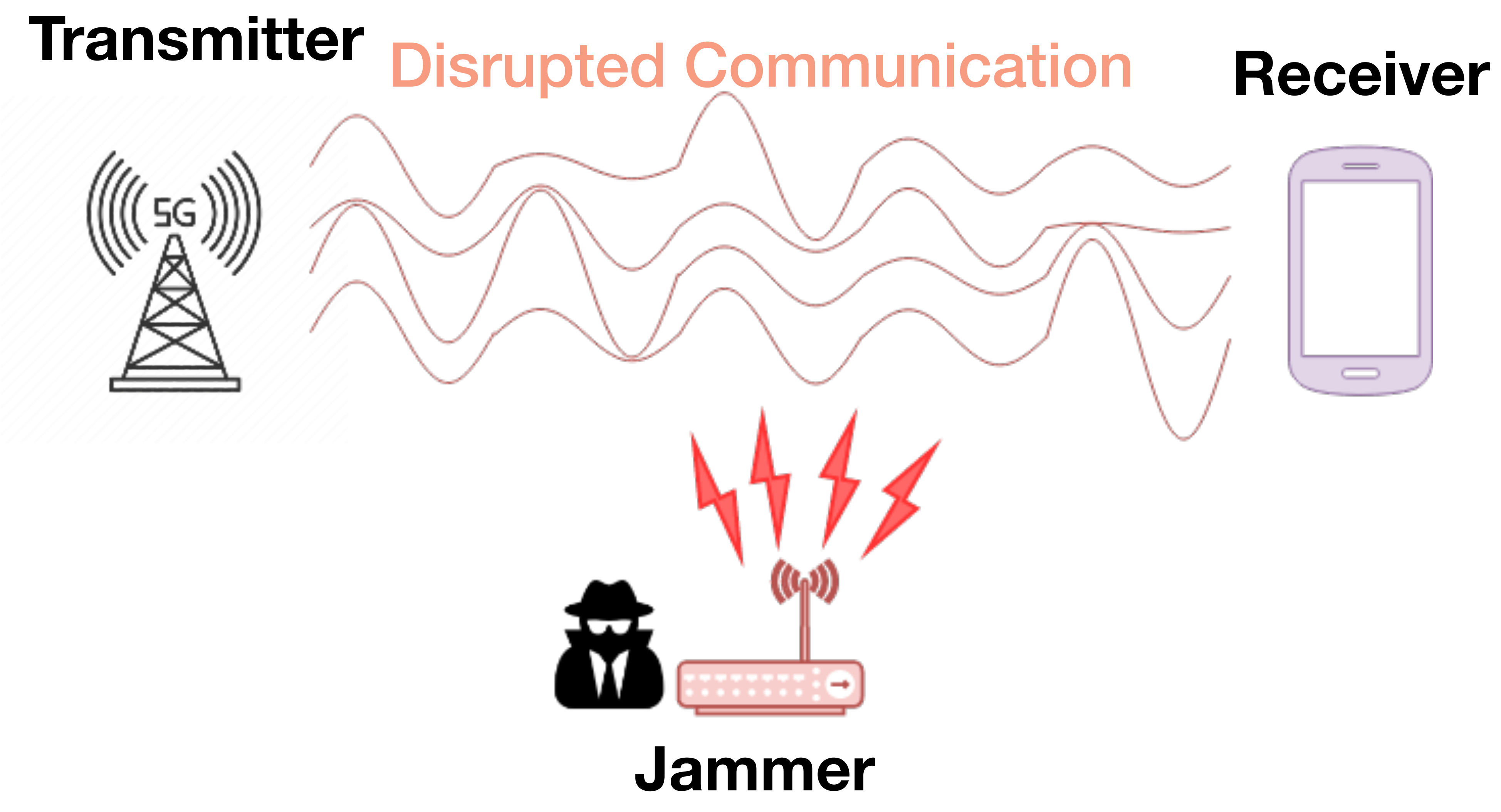
Developing resilience against powerful jamming can help retrieve an acceptable quality of service.

Motivation

- Channel signal strength indicators can easily detect anomalies but cannot help recover transmitted data.
- This causes heavy retransmissions, added latency, power consumption, degradation of QoS, etc.





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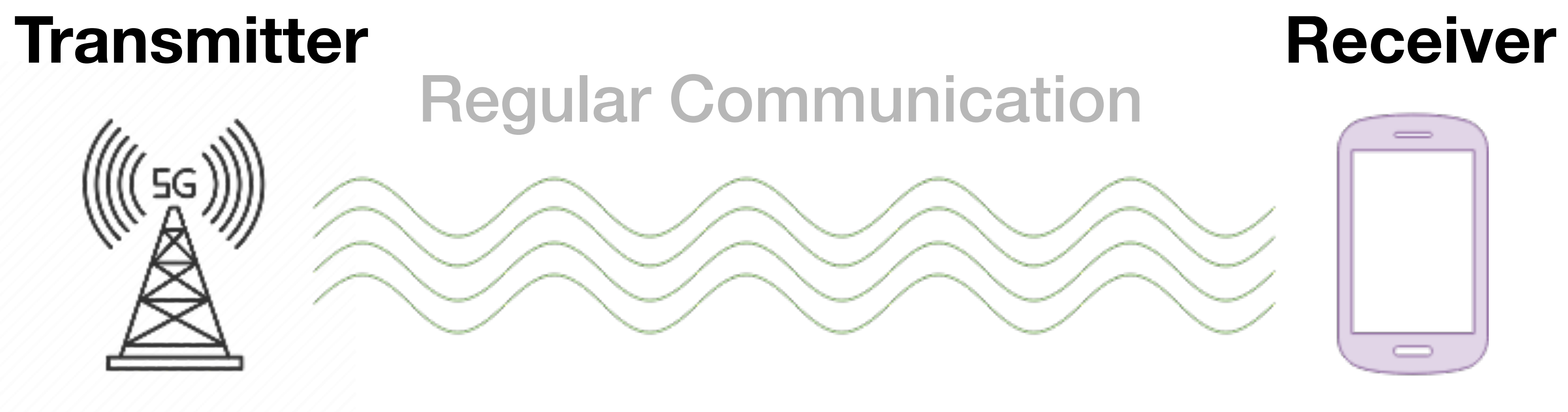

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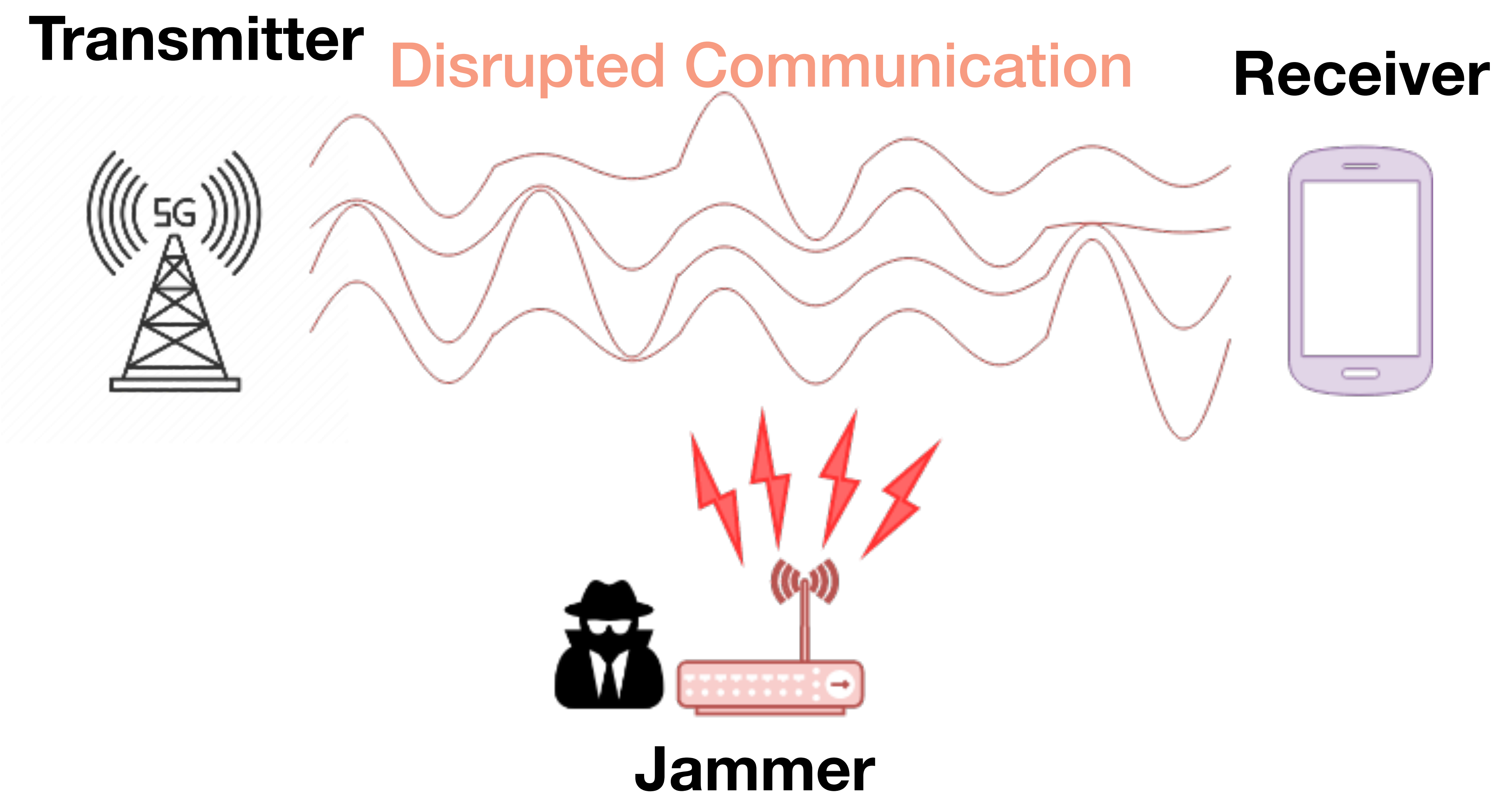

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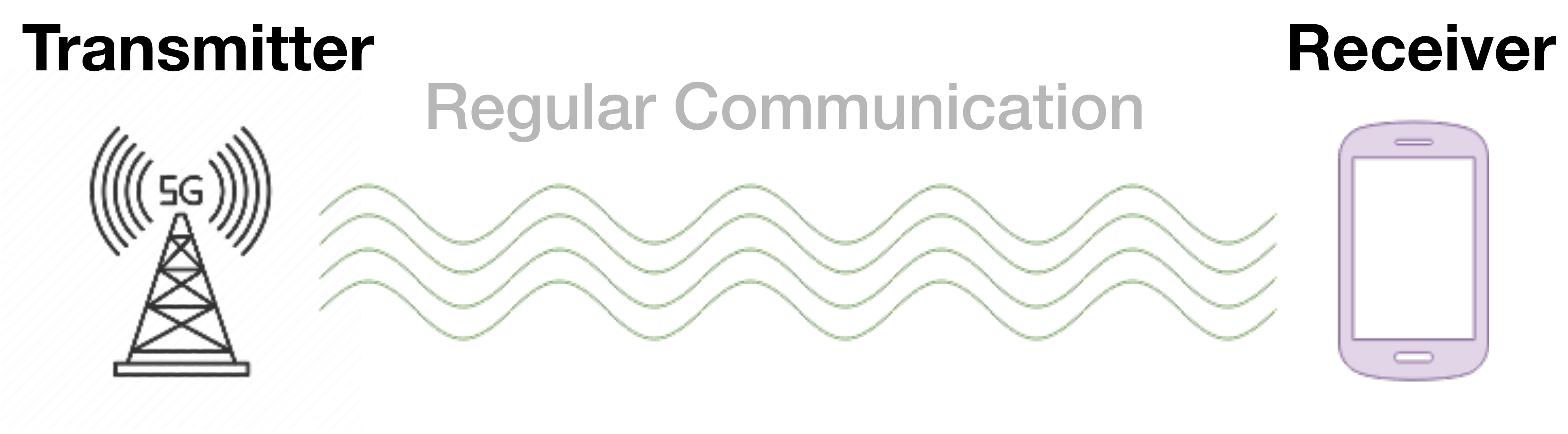
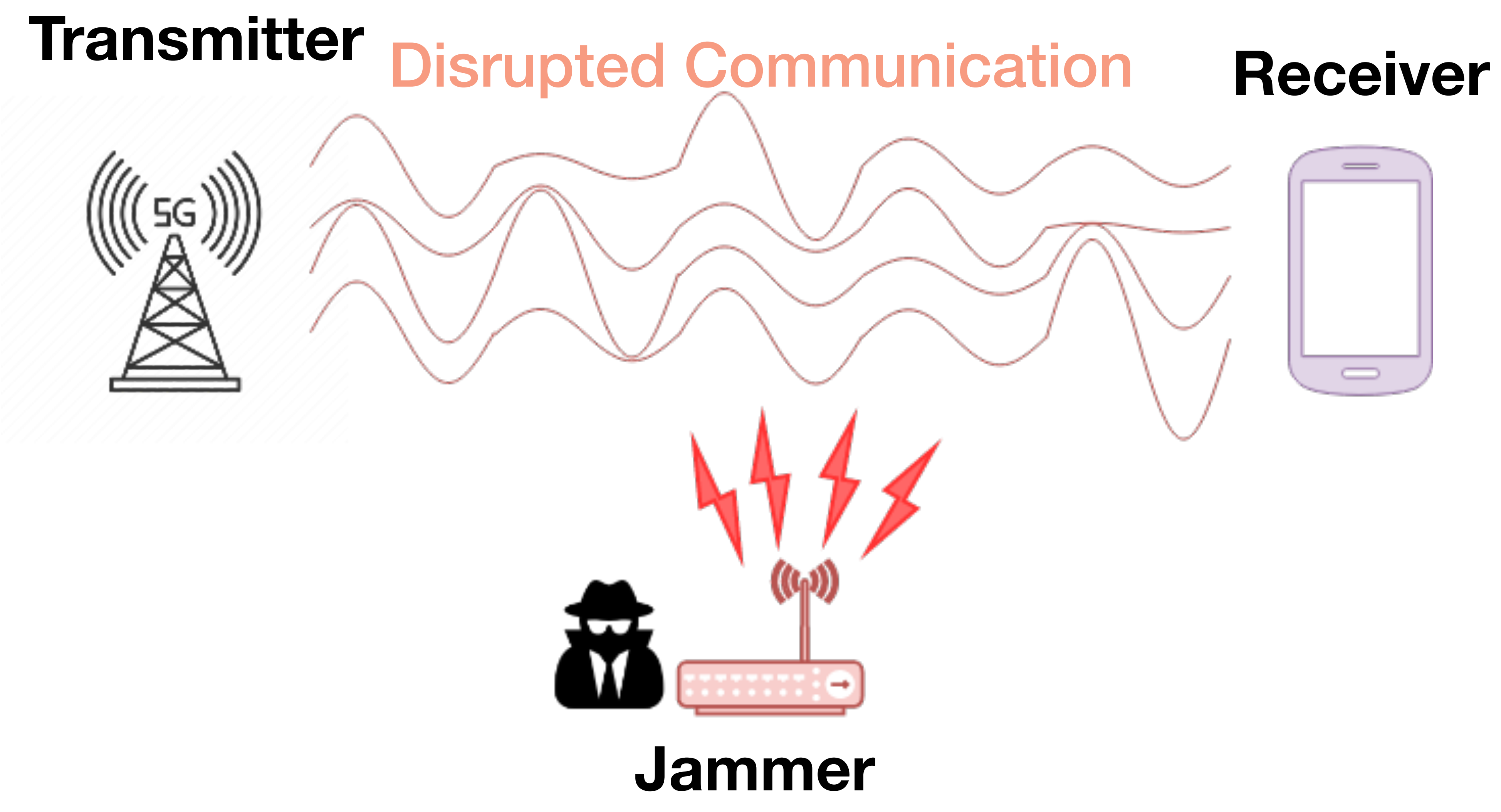


- Our purpose is to add resilience against powerful jamming events.

- We aim to develop an error correction algorithm with data recovery capabilities under powerful adversarial conditions.
- Our proposal is in conjunction with the Guessing Random Additive Noise Decoding (GRAND) algorithm, which can work with any codebook.



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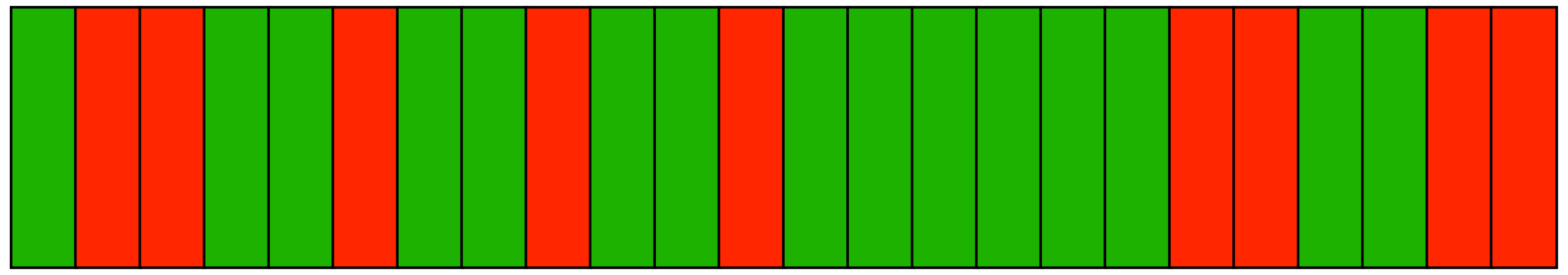
❖ We propose a jamming-resilient algorithm based on GRAND:

Transmitted Jammed Package



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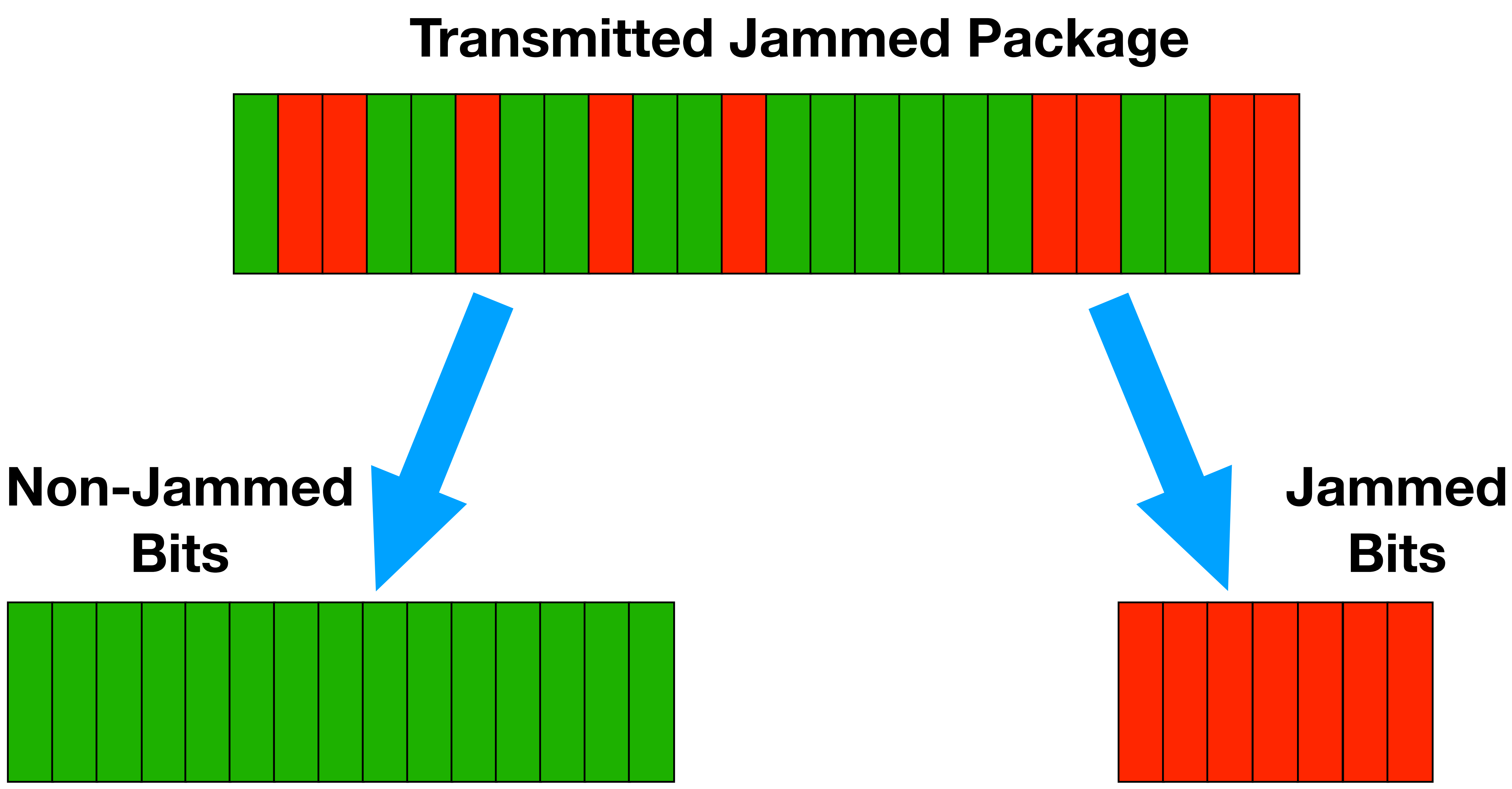
  - First, the jammed bits are identified and separated from the rest of the transmission.



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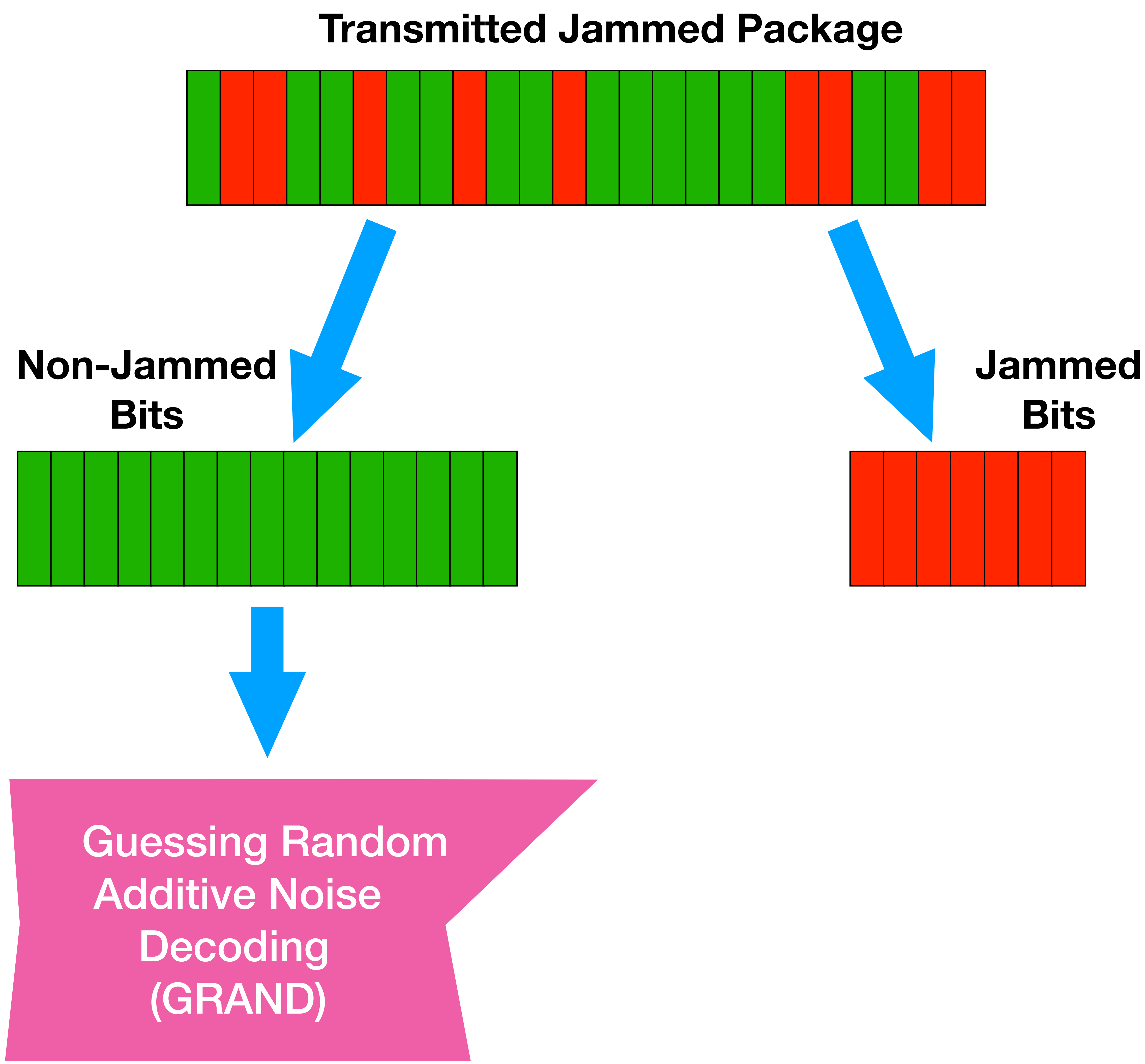

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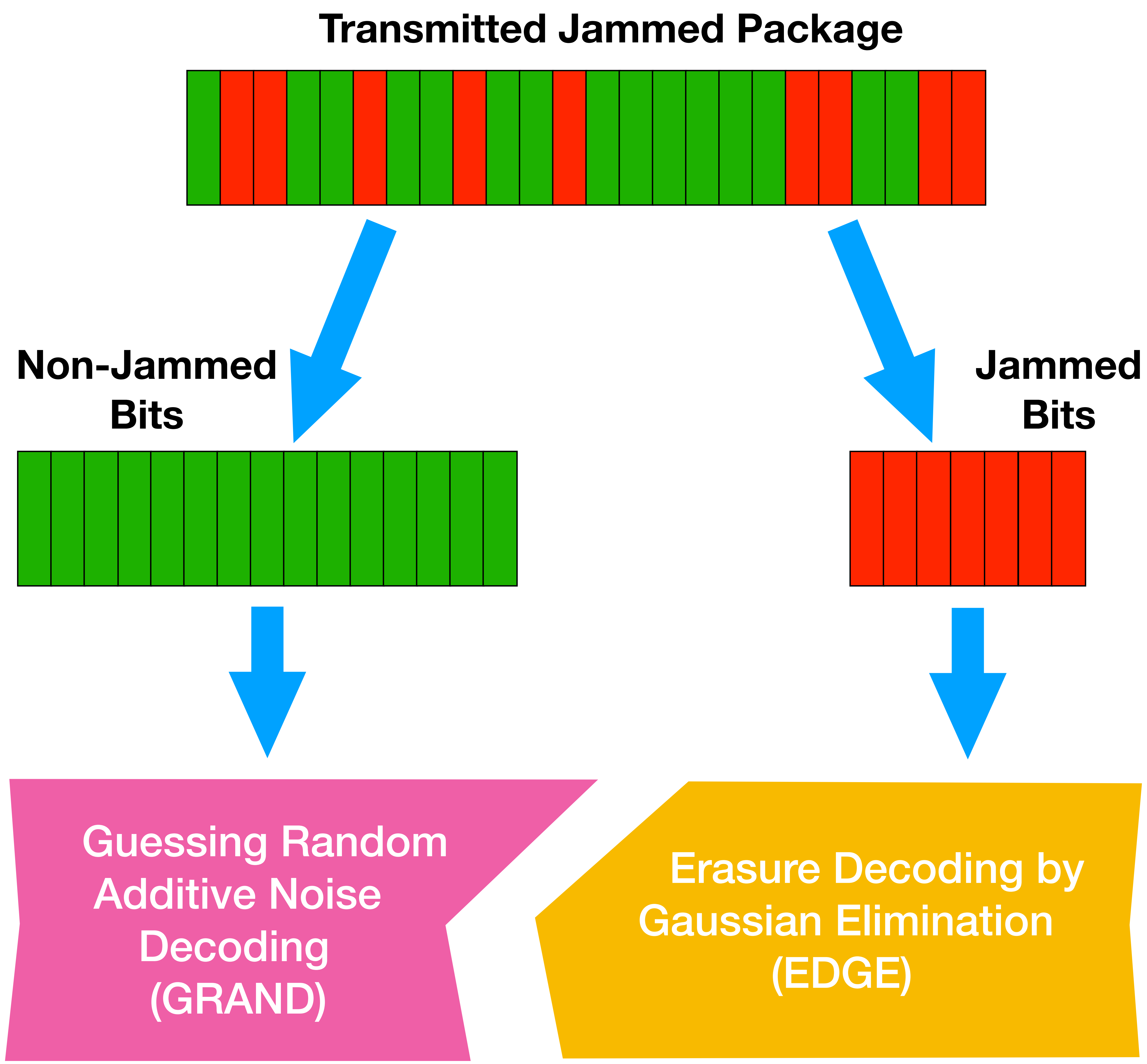

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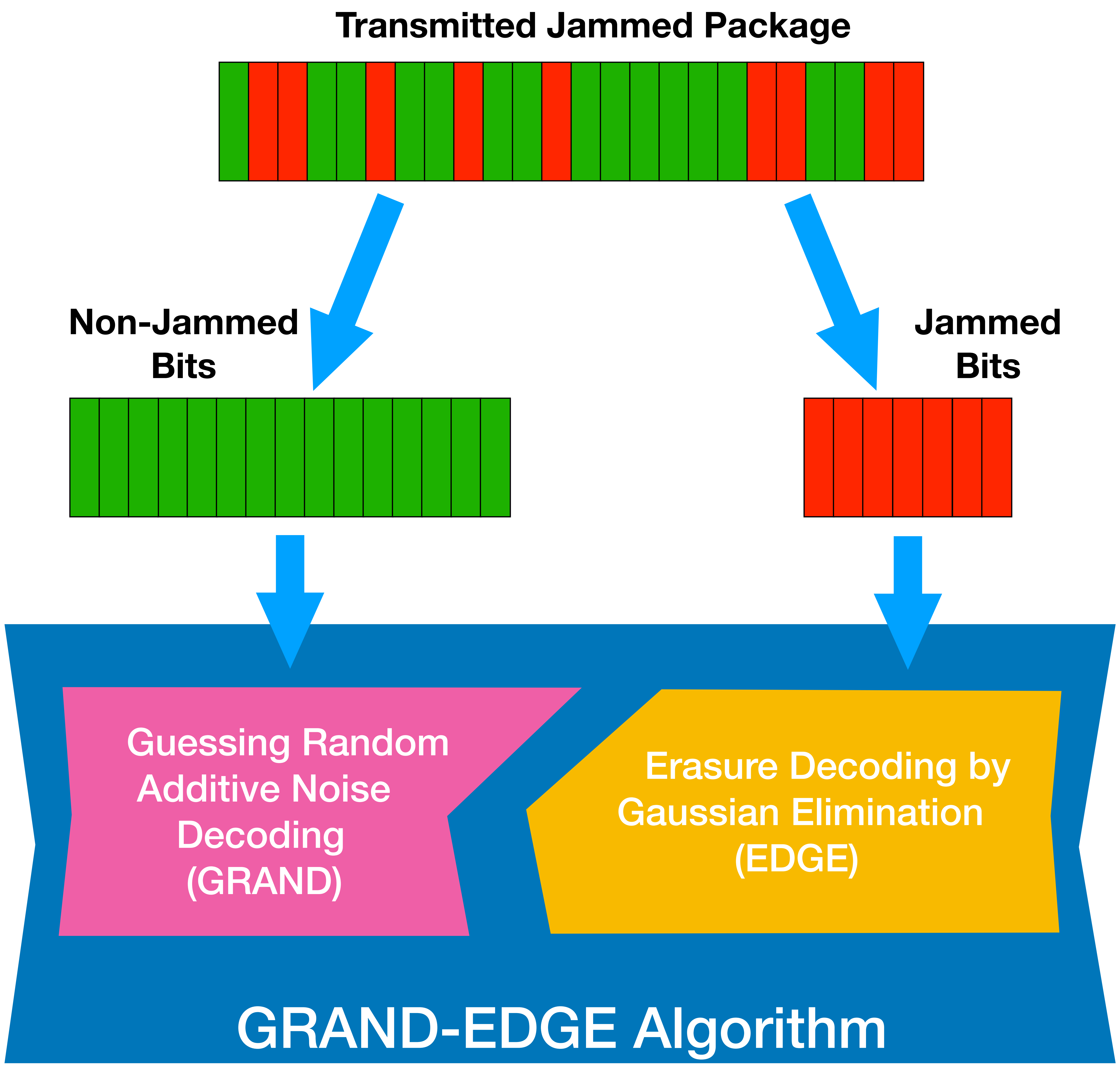
The new algorithm is called the GRAND-EDGE algorithm.



The GRAND Algorithm Family

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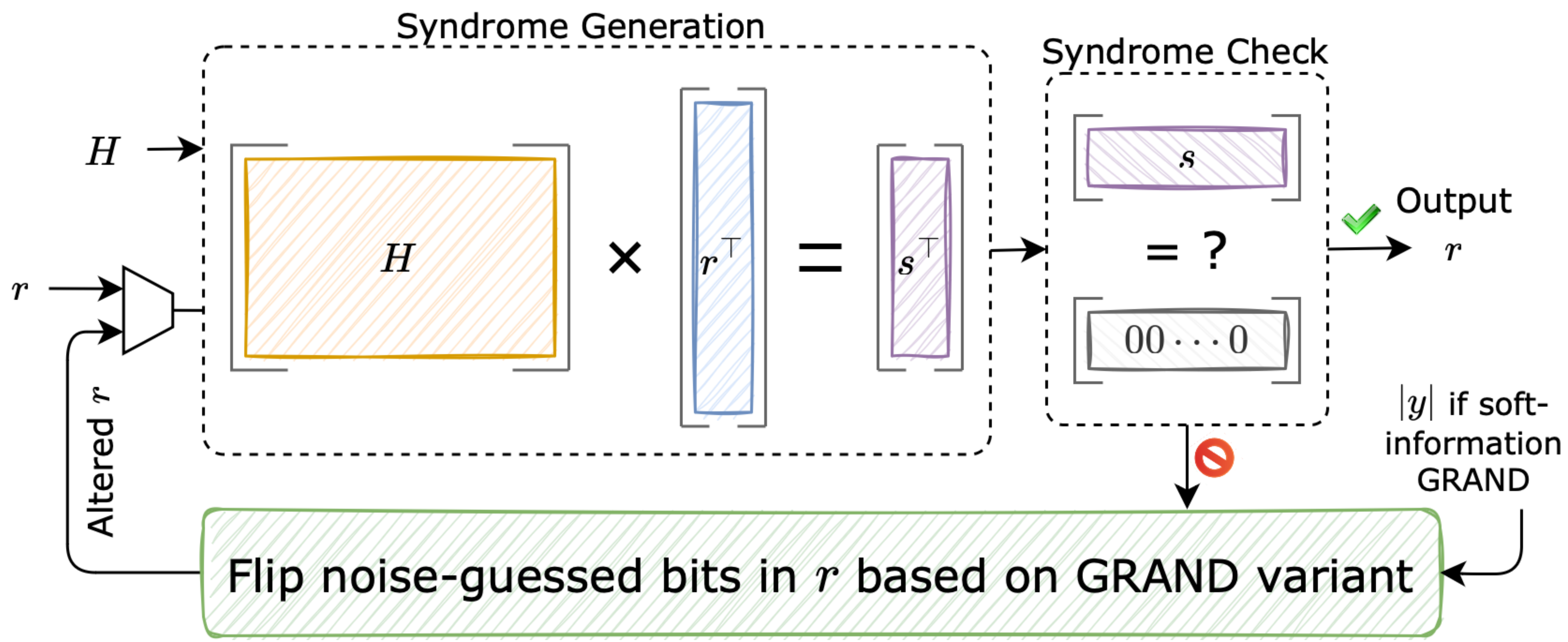
- A syndrome check,
- On a failed syndrome, guessing the noise pattern based on an agenda.
- The ‘agenda’ determines the variant of GRAND.



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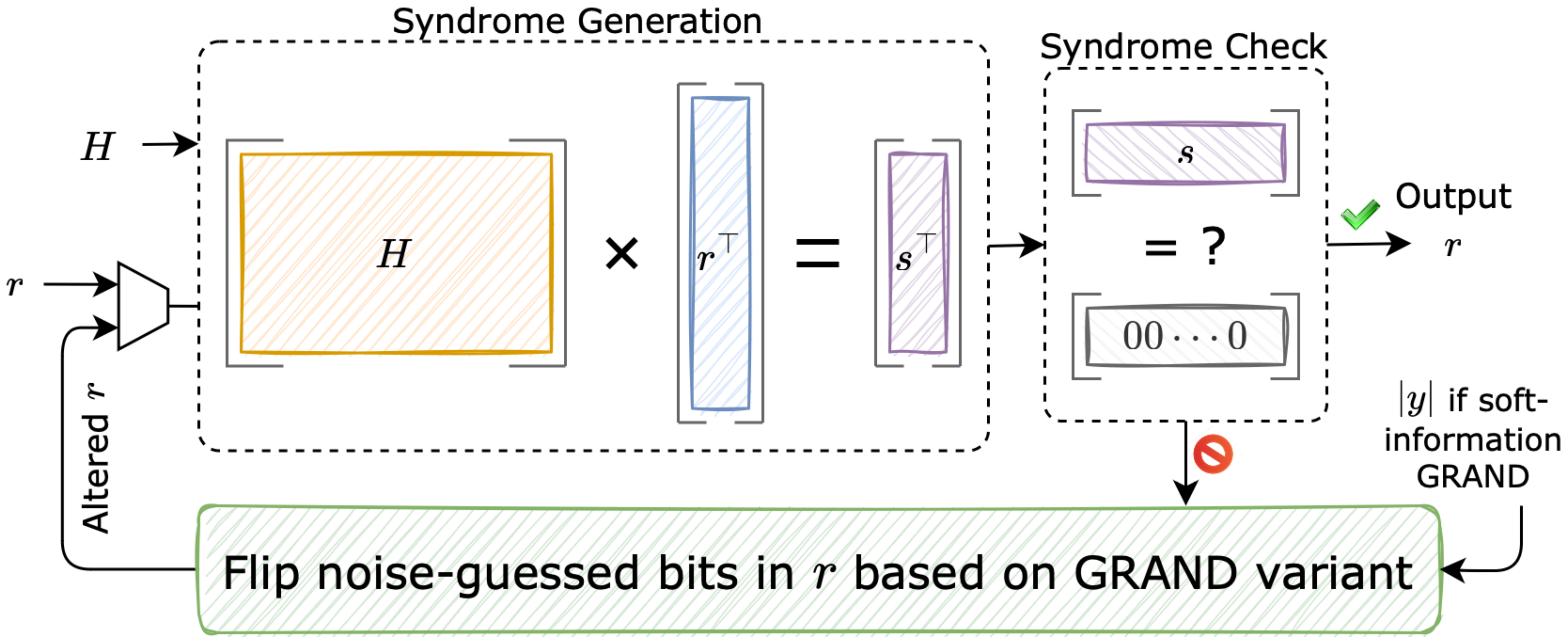
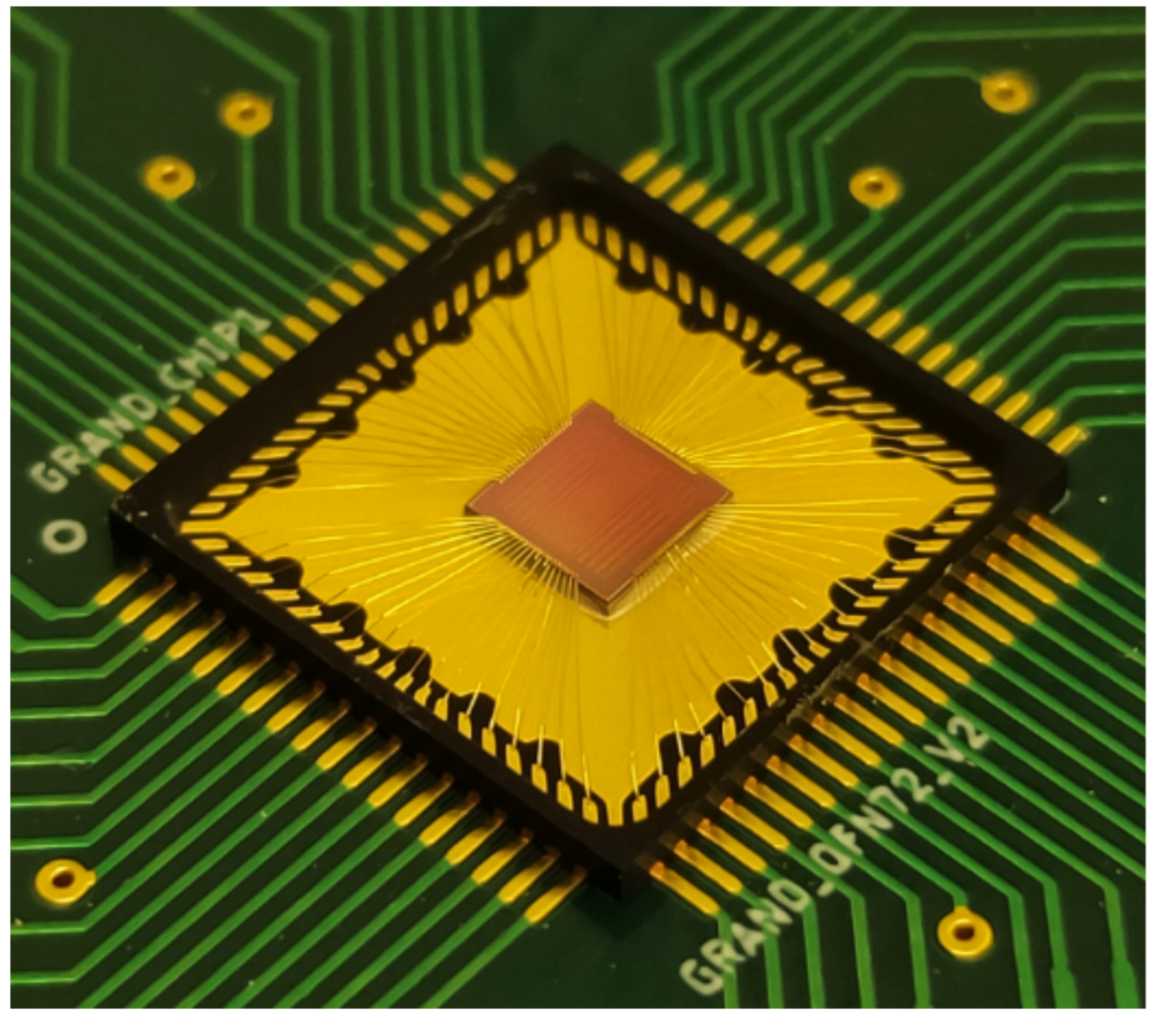
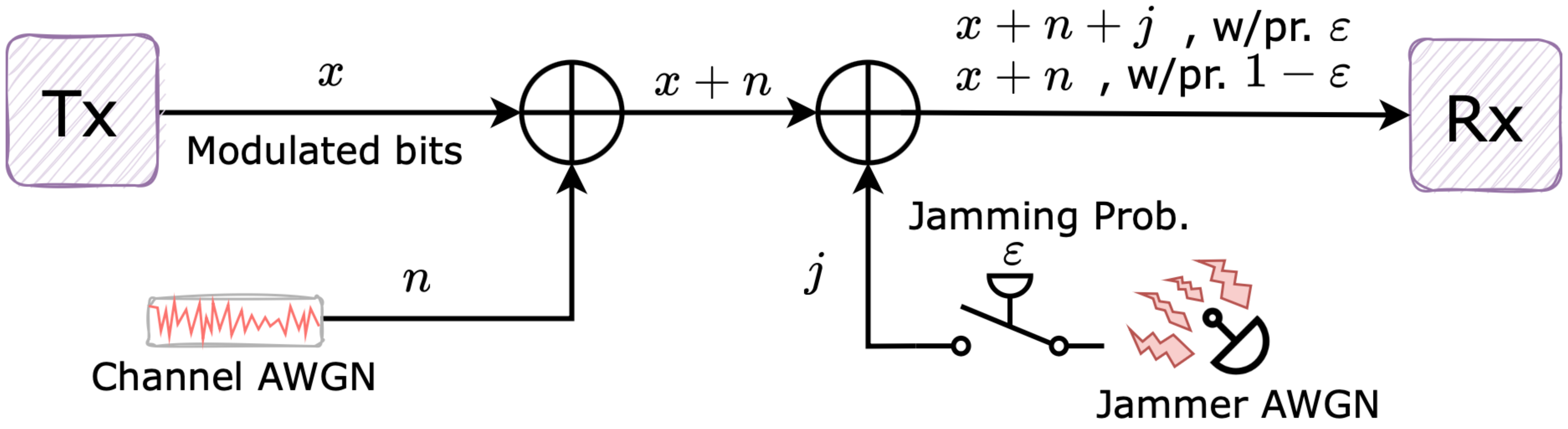




- In this work, we consider:
  - Hard-information GRAND, and
  - Soft-information GRAND (ORBGRAND).

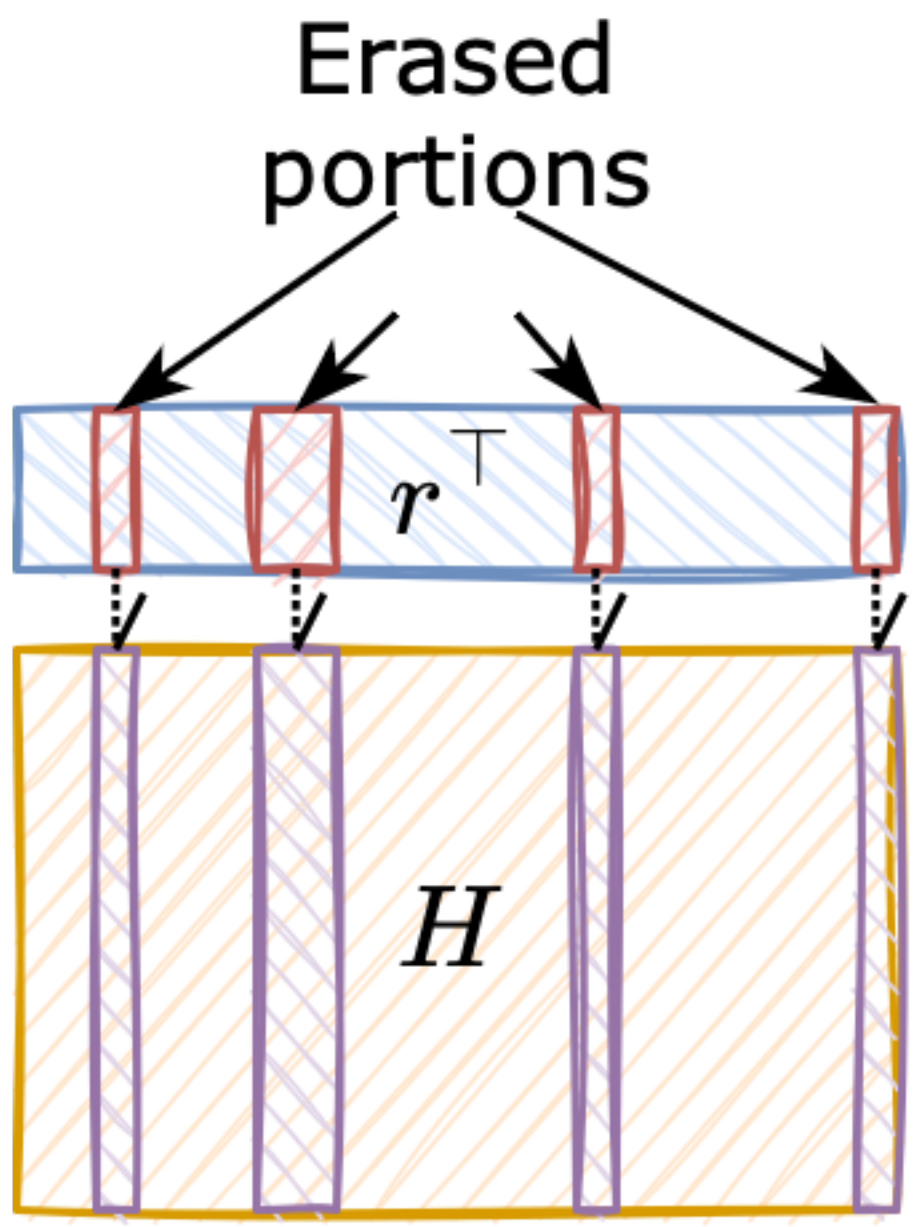
Adversary Channel Model

- We consider an AWGN channel model that is randomly disrupted by a powerful jammer.
- The jammer instance j, which is activated by a probability ϵ, may be added to the transmitted signal.
- The jammer can be modeled as AWGN but with far greater variance.
- If the signal is far stronger than typical, it is considered jammed and its value is not trusted.



$$y = \begin{cases} x+n+j & \text{with probability } \epsilon; \\ x+n & \text{otherwise.} \end{cases}$$

The EDGE Subroutine



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- Step 1: Align the received codeword (r) with the parity check matrix (H).

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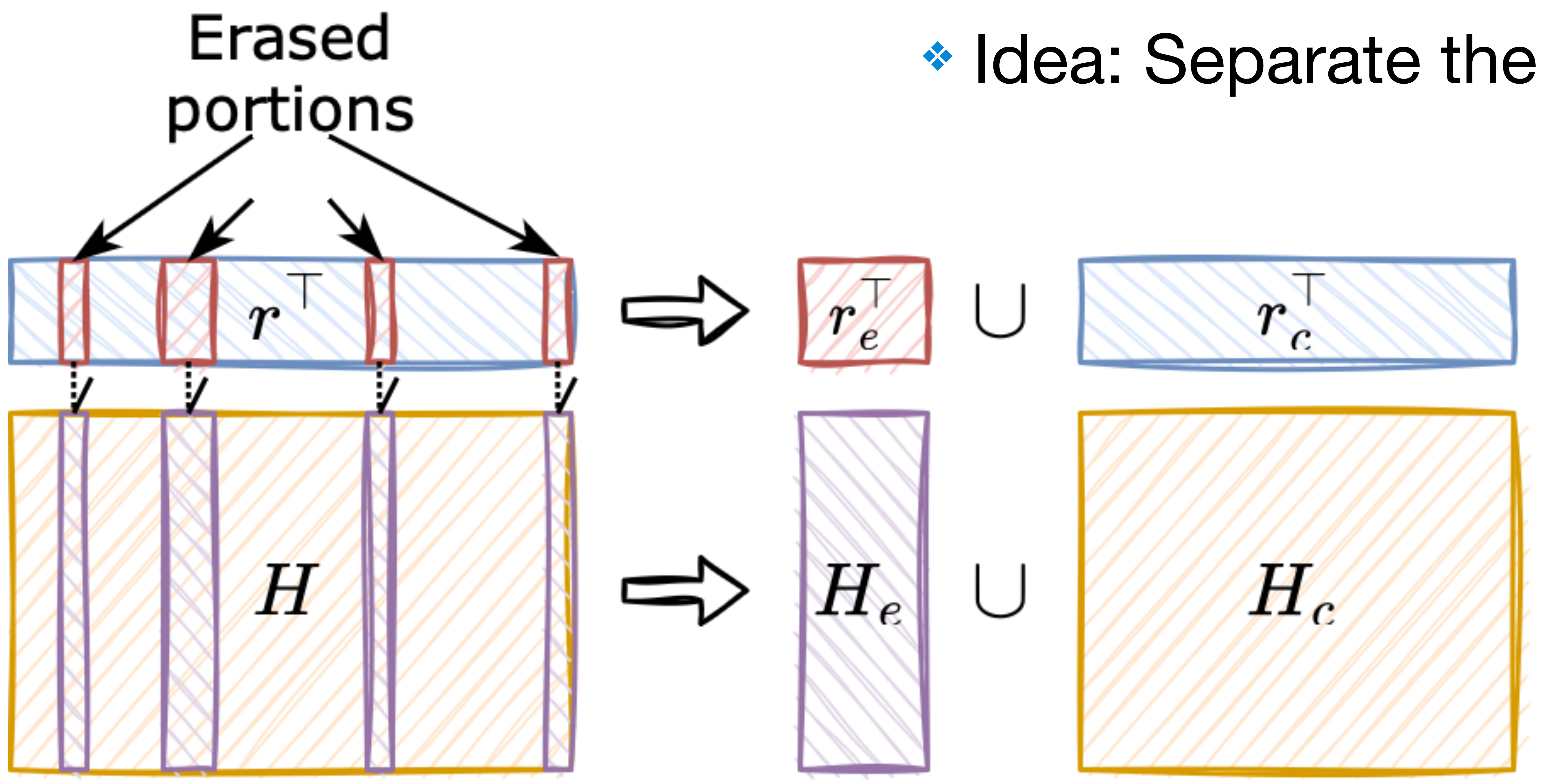

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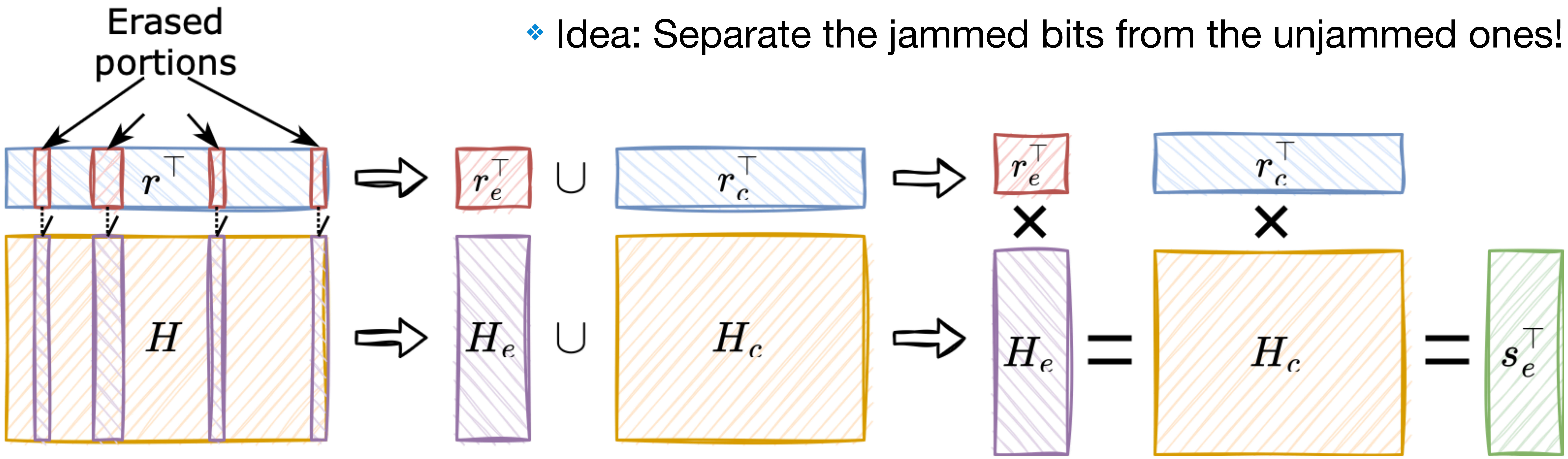

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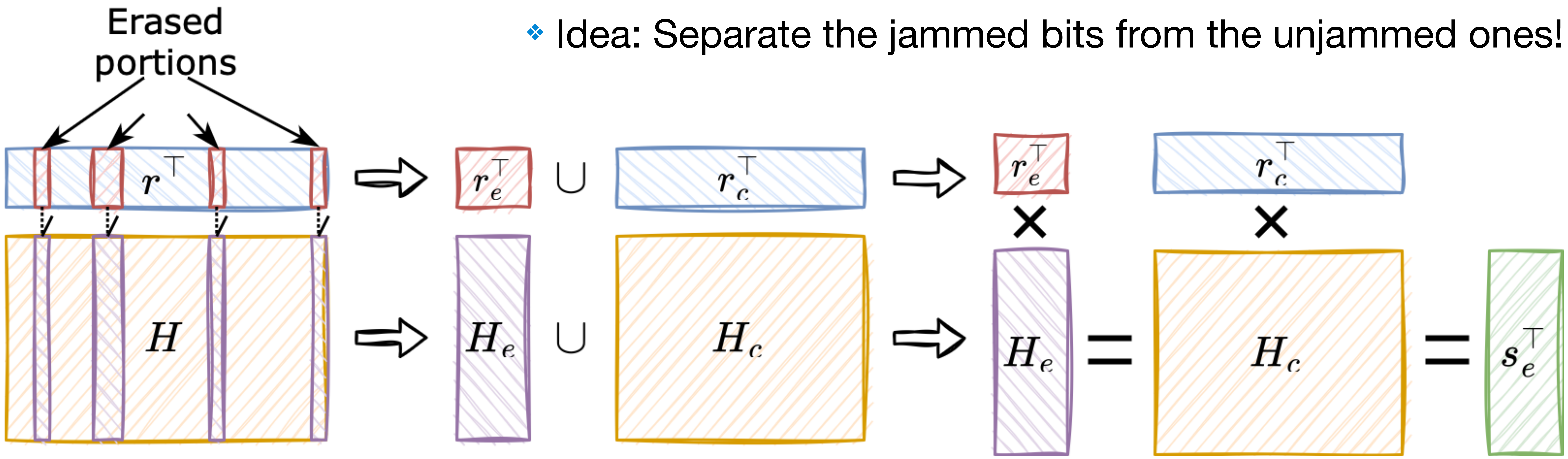

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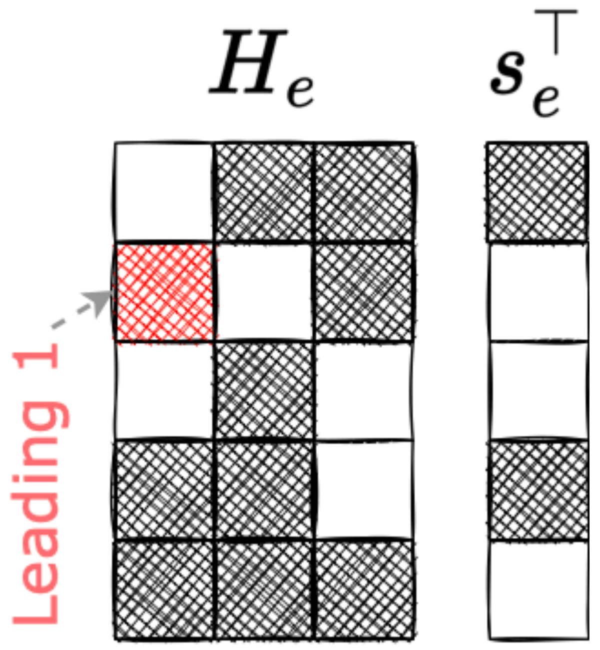
- Step 4: Solve the system of linear equations for the erased received sequence.

$$\mathbf{H_e} \cdot \boxed{\mathbf{r_e}^\top} = \mathbf{s_e}^\top .$$

The Gaussian Elimination Process

- Consider the following example:



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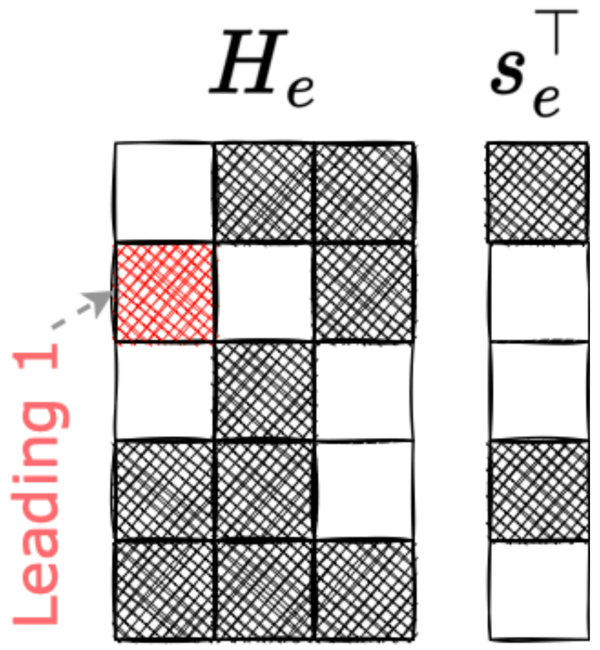

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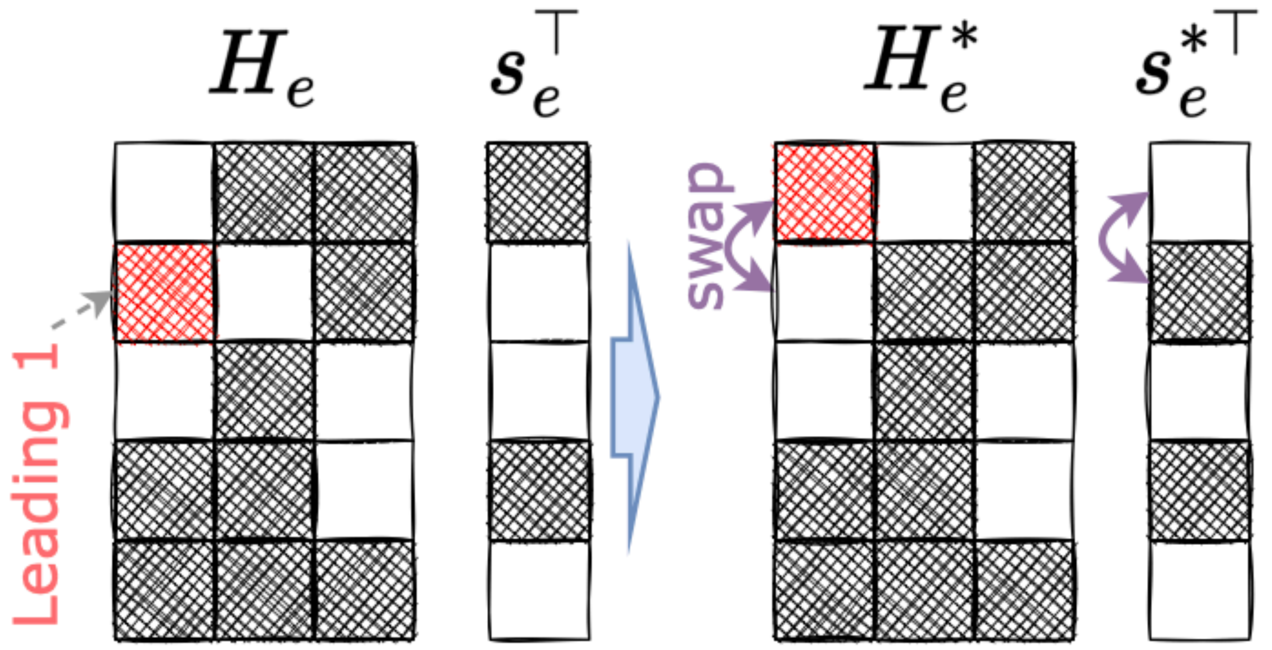

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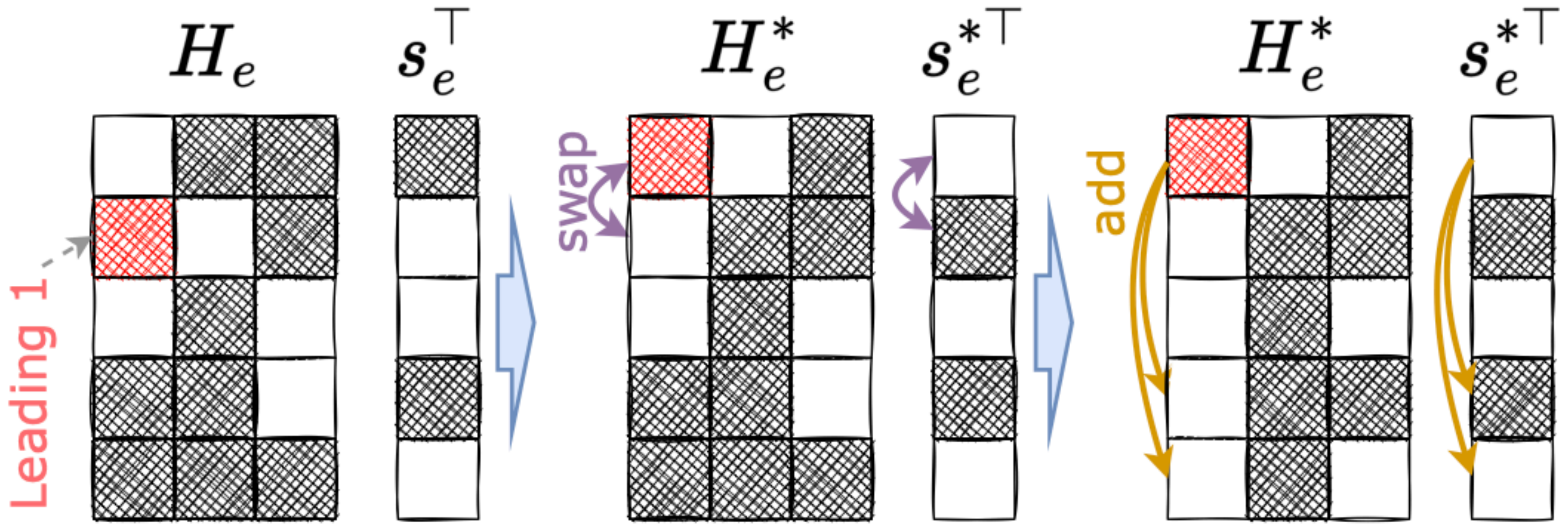

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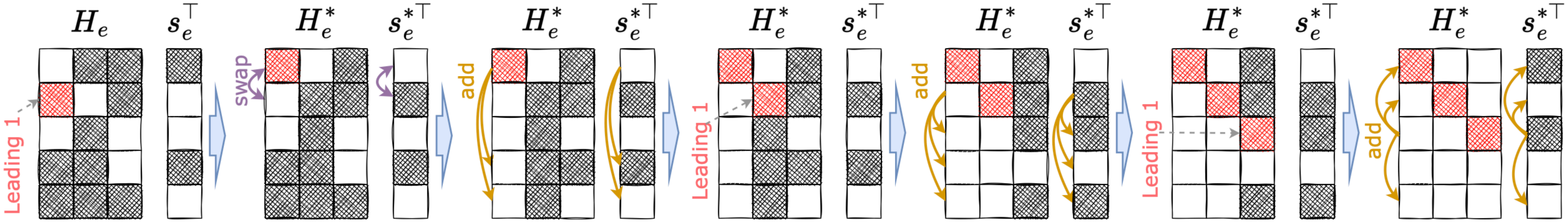

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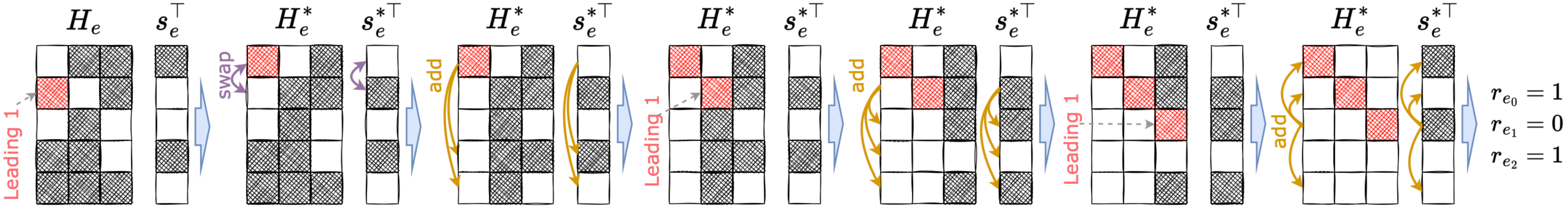

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- Process is repeated until all columns are cleared.
- Resulting modified syndrome vector is the solution key for erased sequences.

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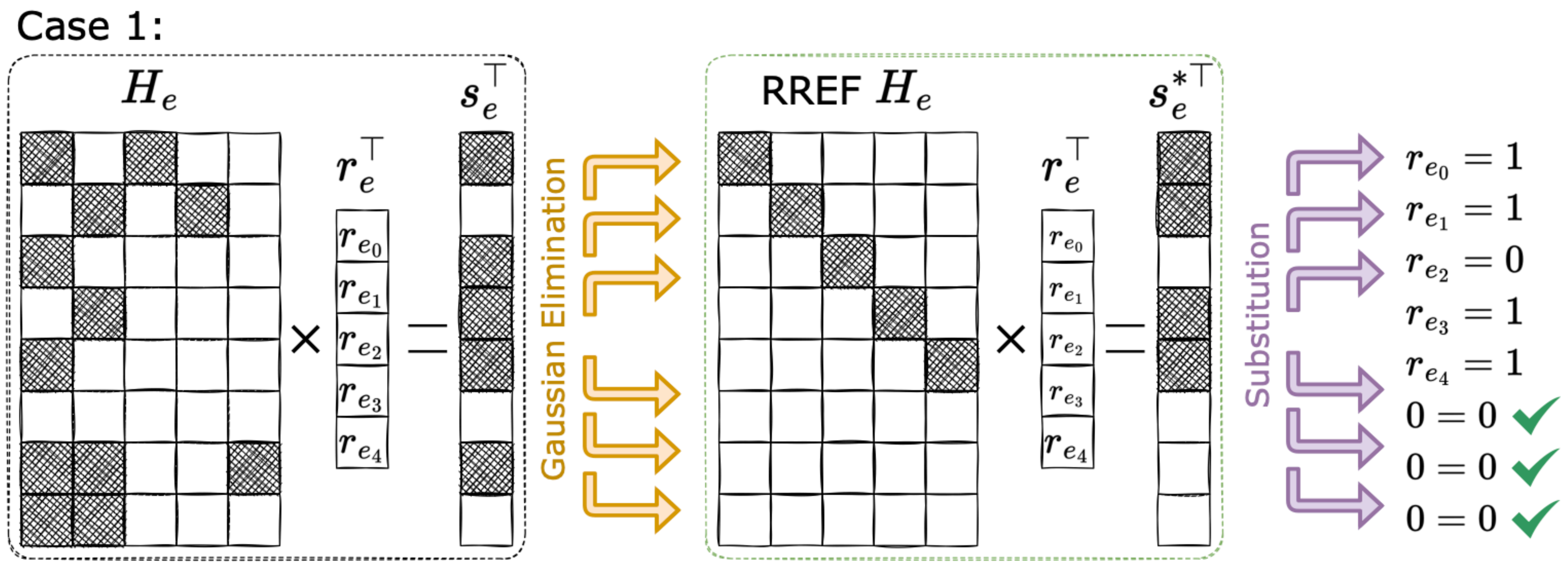
- Add/swap operations of the EDGE can be stored in a matrix E.
- This way, the final erasure syndrome can be directly obtained by

$$\mathbf{s}_{\mathbf{e}}^{*\top} = \mathbf{E} \cdot \mathbf{s}_{\mathbf{e}}$$

The GRAND-EDGE Algorithm Family



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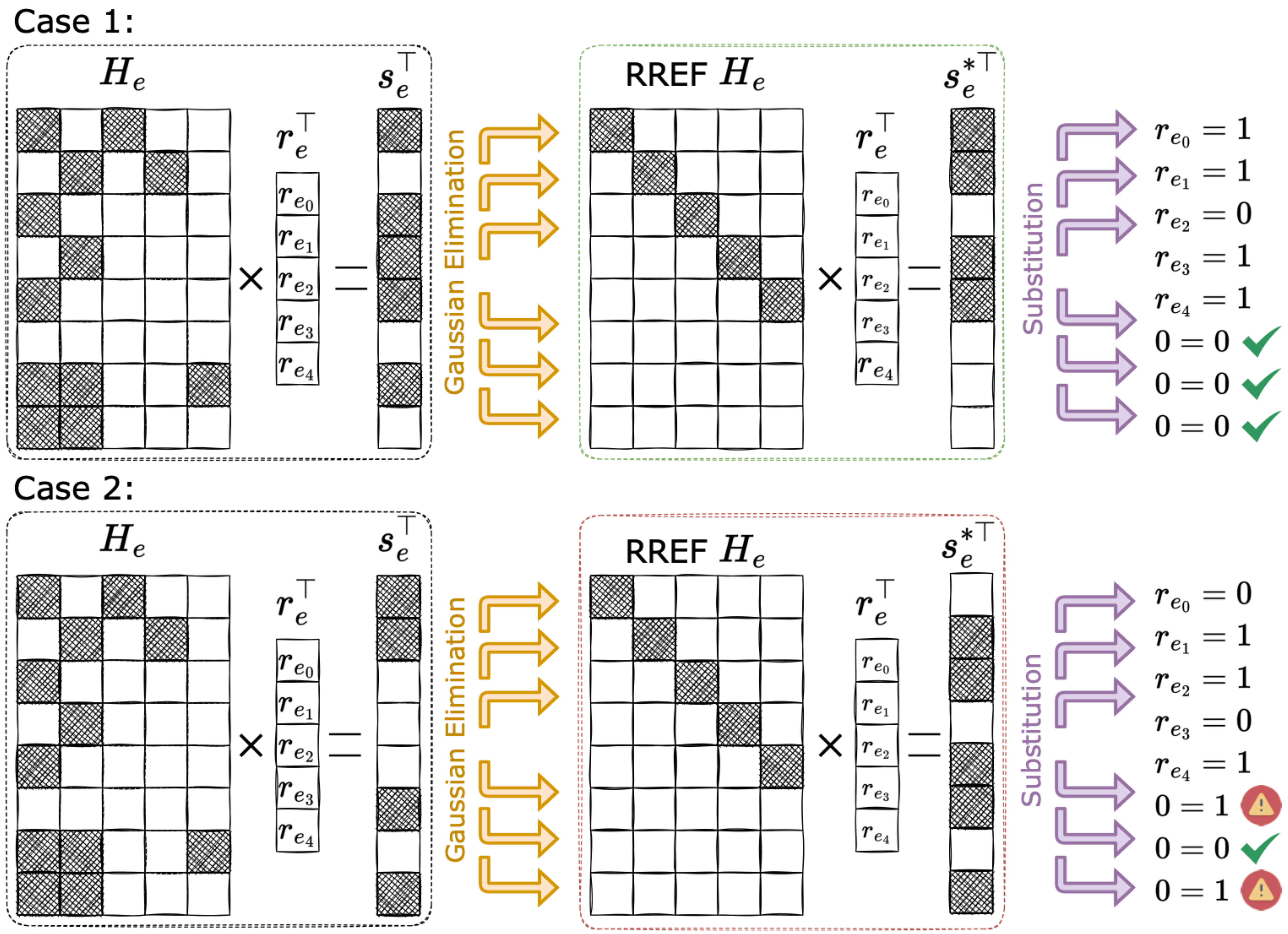

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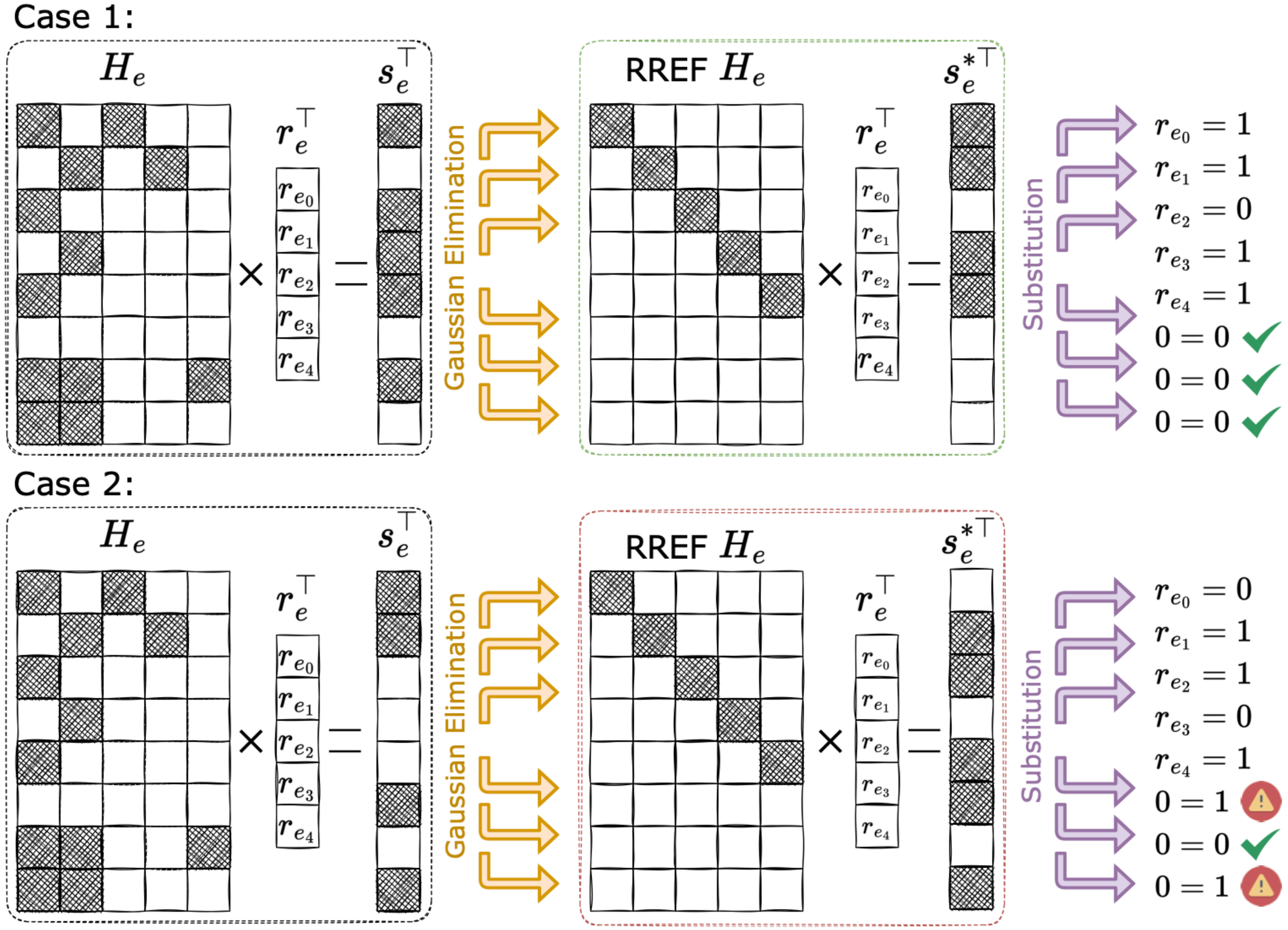

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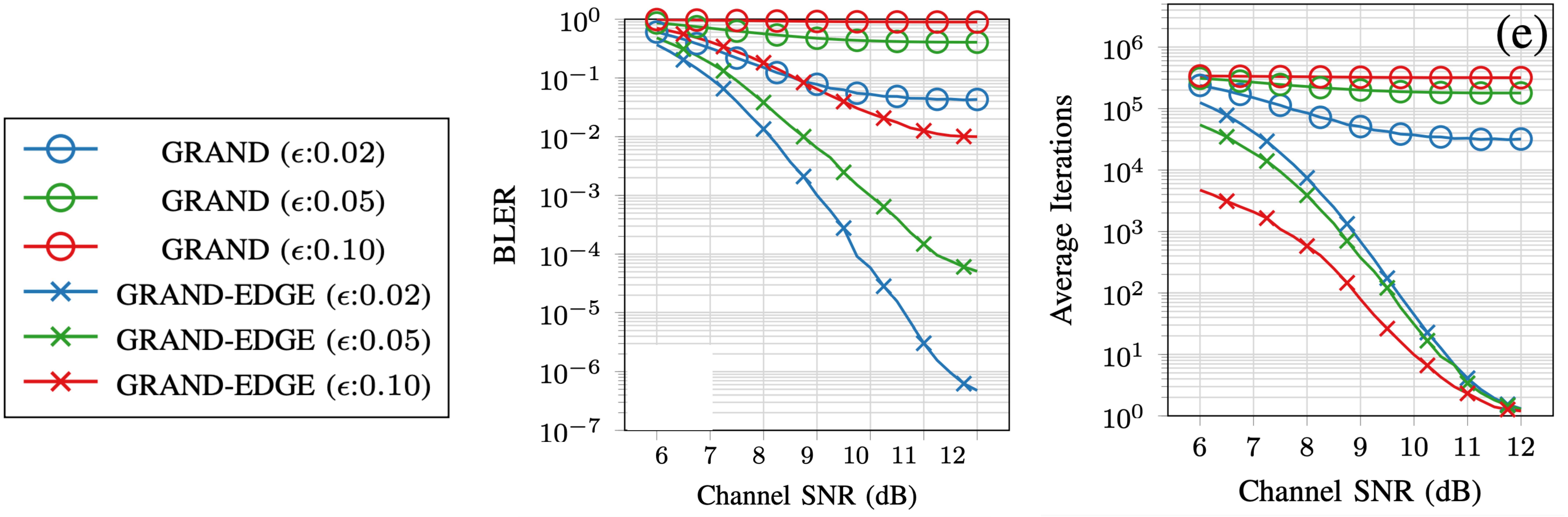
- Keep iterating until EDGE passes or a maximum number of iterations is reached.

Performance Assessment: GRAND-EDGE



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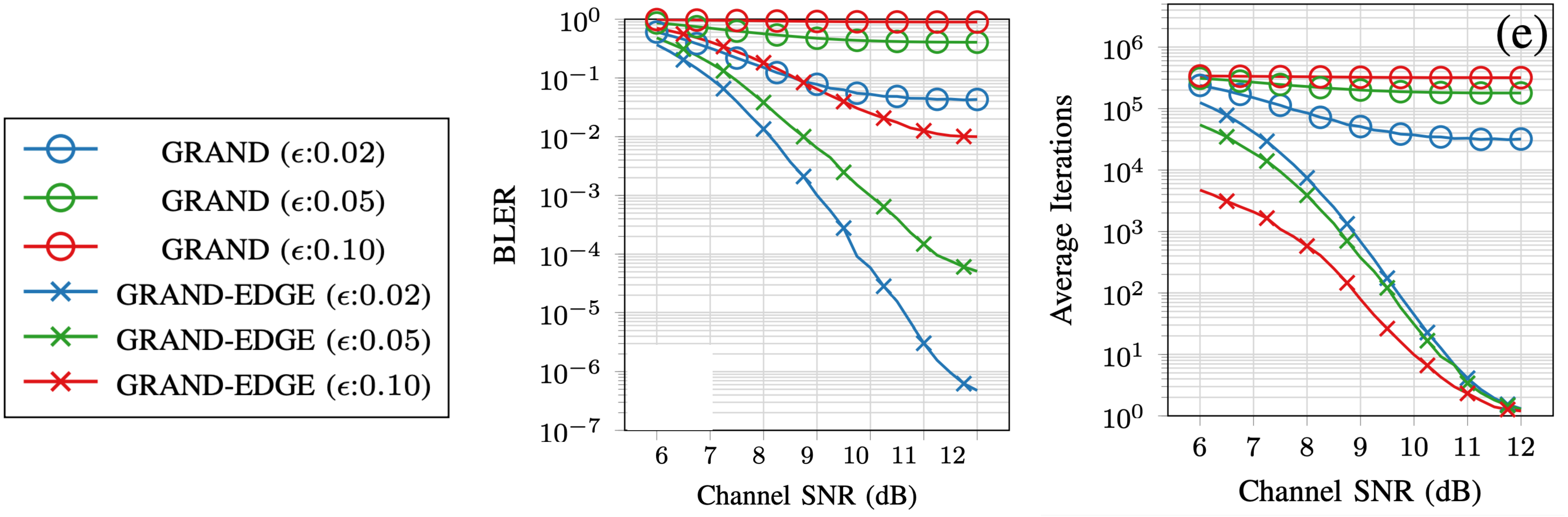

- Performance evaluation was carried out using Random Linear Codes.
- GRAND-EDGE and ORBGRAND-EDGE are created and simulated.
- Block Error Rate improvement of five orders of magnitude.
- Average number of iterations improves more than five orders of magnitude.

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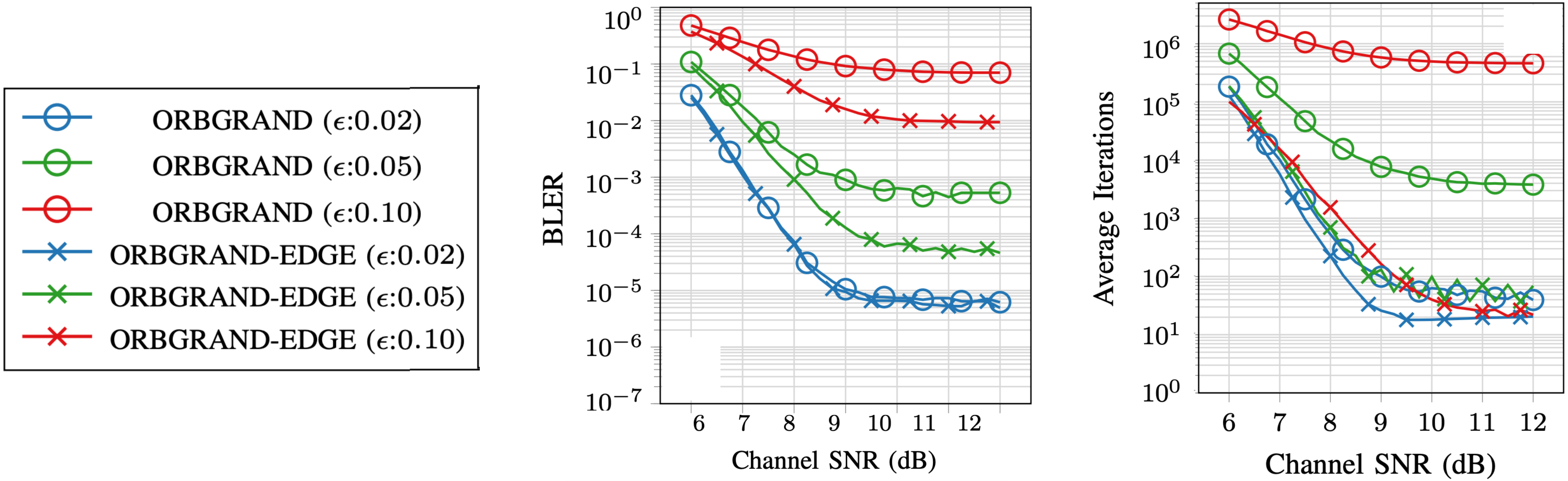
Performance Assessment: ORBGRAND-EDGE



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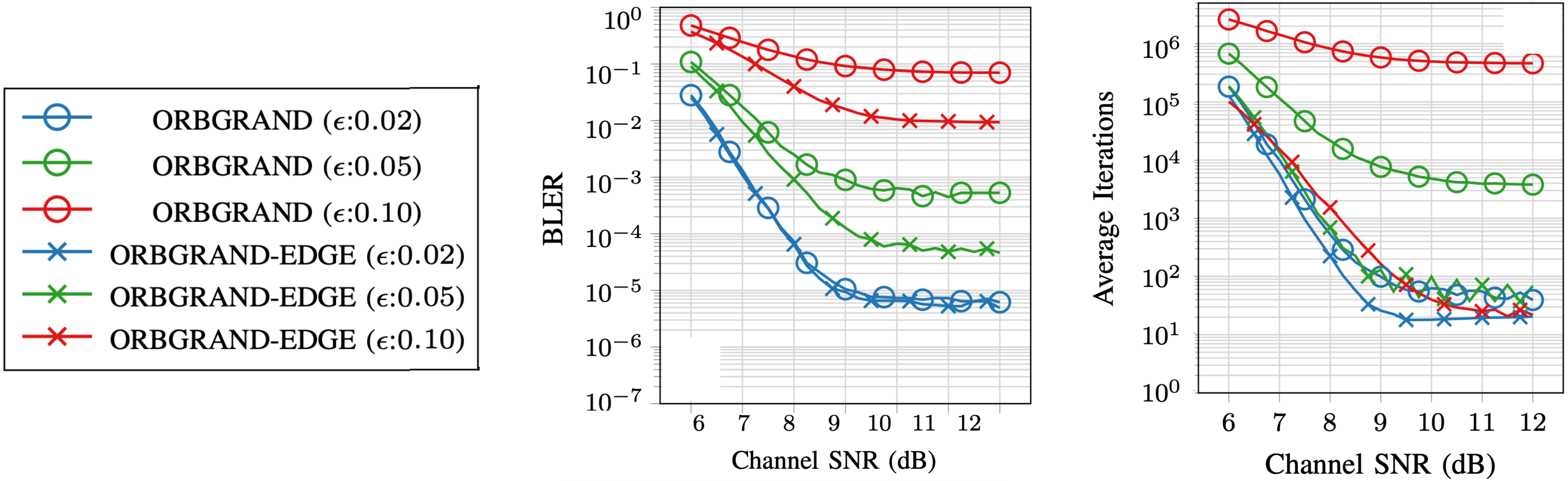

- BLER performance: Up to one order of magnitude improvement
- Average number of iterations: Up to one order of magnitude improvement.
- ORBGRAND scopes flipping bits in a limited way which in turn limits the performance improvement.
- The EDGE algorithm can be extended to any other variant of GRAND.

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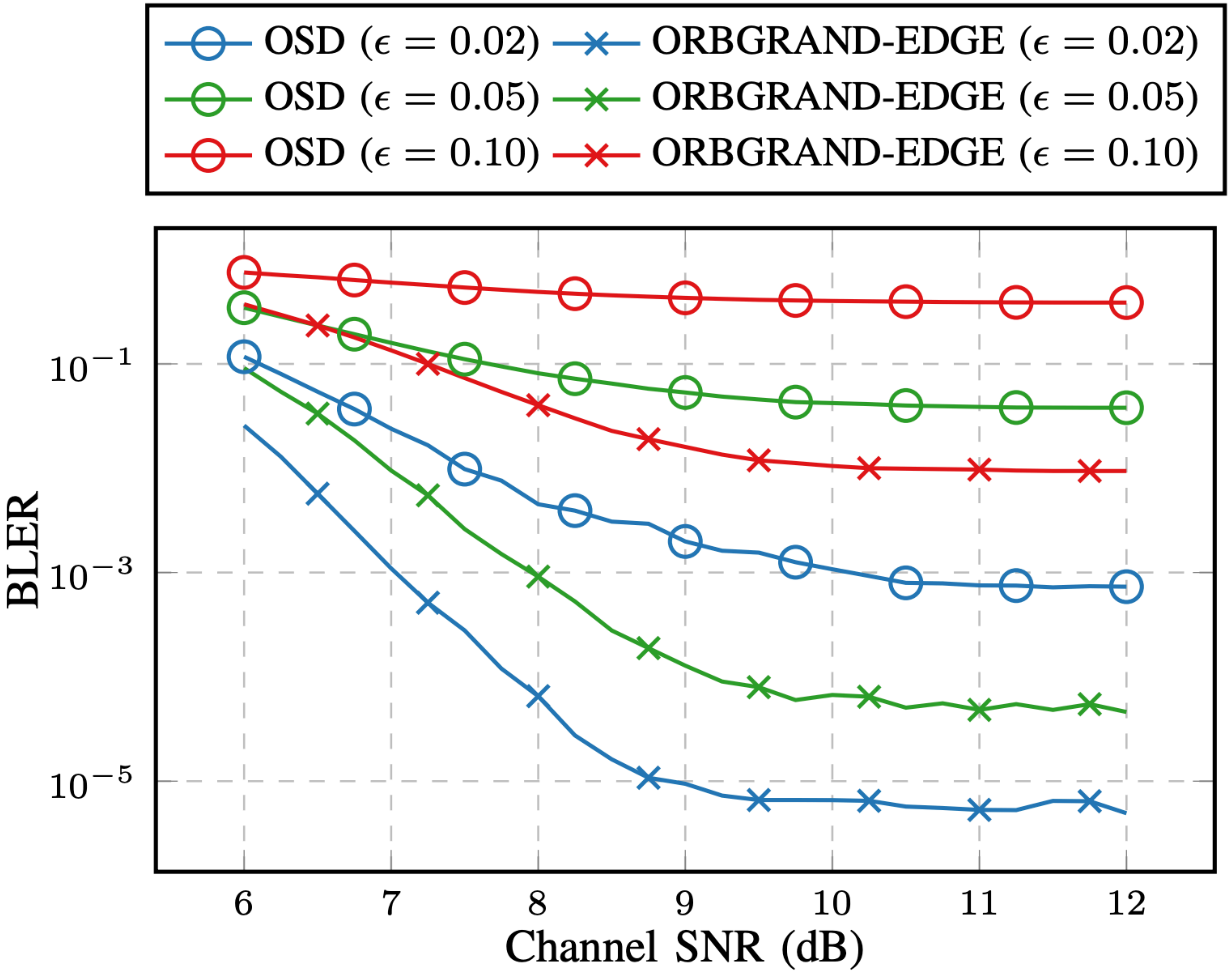
Performance Assessment: GRAND-EDGE vs. OSD



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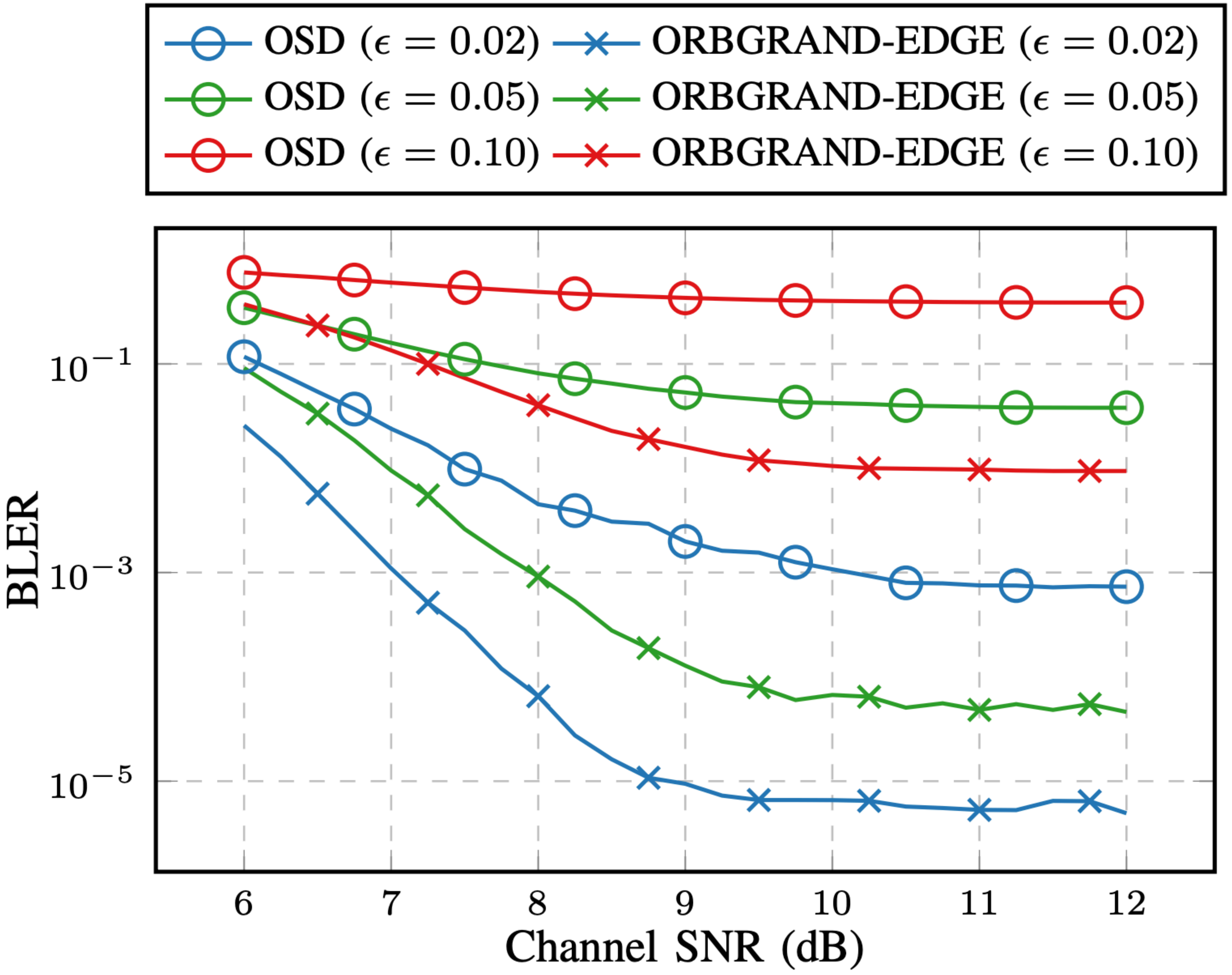

- RLC[128,105] code is used.
- OSD performs GE over k columns, whereas GRAND-EDGE does so over $N-k$ columns (far less for rates of interest).
- OSD requires a new GE for each iteration, whereas GRAND-EDGE requires only one per iteration.
- GRAND-EDGE is shown to have up to 3 orders of magnitude better BLER than that of OSD.

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- We showed that the syndrome calculation block can be generalized into an erasure decoding, using Gaussian Elimination.
- The yielding algorithm is called the GRAND-EDGE.
- Any variant of GRAND can be used towards the proposed enhancement.
- Simulation results with both hard- and soft-information variants demonstrate substantial gains in error performance and computational complexity under adversarial constraints.

Thank you!