



Vectorized linear approximations for attacks on SNOW 3G

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- ① Motivation
- ② The SNOW 3G Cipher
- ③ Linear Cryptanalysis of SNOW 3G
 - Linear Approximation of FSM
 - Distinguishing Attack
 - Correlation Attack
- ④ Conclusions



Outline

- 1 Motivation**
- 2 The SNOW 3G Cipher
- 3 Linear Cryptanalysis of SNOW 3G
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- 4 Conclusions



Confidentiality and Integrity Protection in Cellular Networks

- ▶ Three standardized algorithms in LTE: SNOW 3G, AES, ZUC
 - ▶ 128-bit security level



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 - ▶ 128-bit security level
- ▶ 5G: 256-bit security algorithms
- ▶ One possible solution: reuse existing algorithms
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- ▶ **Contribution:** give linear cryptanalysis of SNOW 3G
 - ▶ Distinguishing attack 2^{172}
 - ▶ Correlation attack 2^{177}



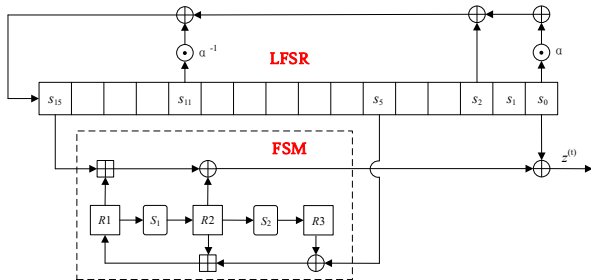
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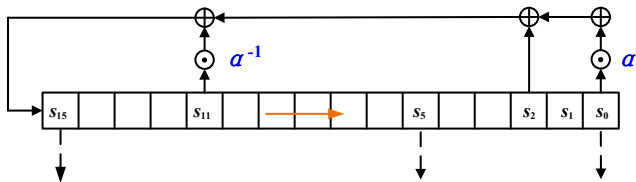
SNOW 3G

- ▶ A stream cipher with a linear part and a non-linear part



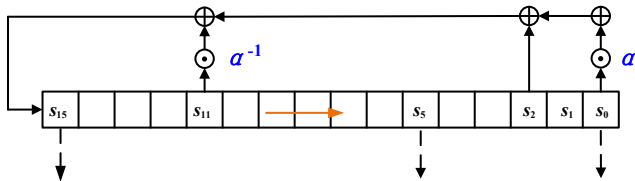
- ▶ **Linear part:** linear feedback shift register (LFSR)
- ▶ **Non-linear part:** finite state machine (FSM)

LFSR in SNOW 3G



- ▶ Defined over $GF(2^{32})$, 16 cells \times 32 bits / cell = 512 bits

LFSSR in SNOW 3G

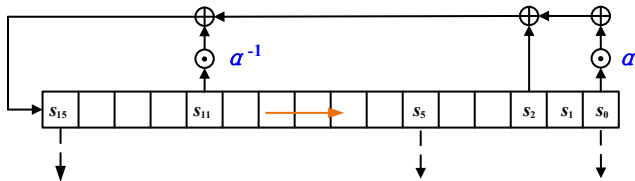


- ▶ Defined over $GF(2^{32})$, 16 cells \times 32 bits / cell = 512 bits
- ▶ **Feedback polynomial:**

$$P(x) = \alpha x^{16} + x^{14} + \alpha^{-1} x^5 + 1 \in GF(2^{32})[x]$$

- ▶ α is a root of a polynomial in $GF(2^8)[x]$

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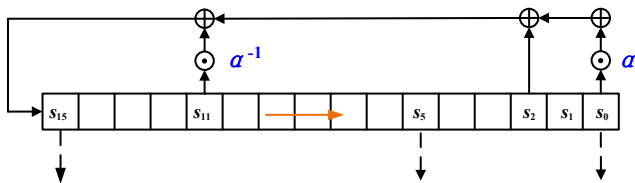
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- ▶ **LFSR update:**

$$s_i^{(t+1)} = s_{i+1}^{(t)} \quad (0 \leq i \leq 14),$$
$$s_{15}^{(t+1)} = \alpha^{-1} s_{11}^{(t)} + s_2^{(t)} + \alpha s_0^{(t)}.$$



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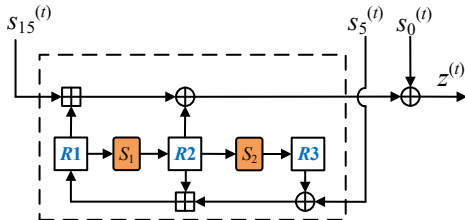
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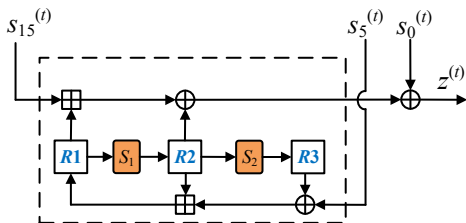
- ▶ $s_{15}^{(t)}, s_5^{(t)}, s_0^{(t)}$ used to update FSM and generate keystream



FSM in SNOW 3G

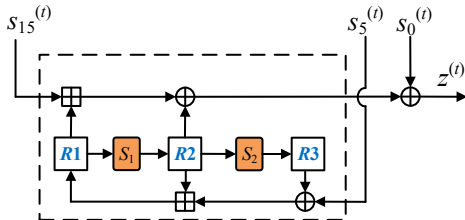


FSM in SNOW 3G



► Keystream block: $z^{(t)} = (R1^{(t)} \boxplus s_{15}^{(t)}) \oplus R2^{(t)} \oplus s_0^{(t)}$

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- ▶ Keystream block: $z^{(t)} = (R1^{(t)} \boxplus s_{15}^{(t)}) \oplus R2^{(t)} \oplus s_0^{(t)}$
- ▶ FSM update:

$$R1^{(t+1)} = R2^{(t)} \boxplus_{32} (R3^{(t)} \oplus s_5^{(t)})$$

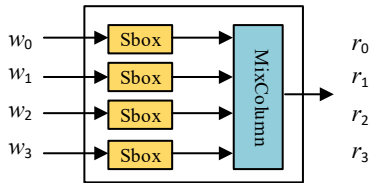
$$R2^{(t+1)} = S_1(R1^{(t)})$$

$$R3^{(t+1)} = S_2(R2^{(t)})$$

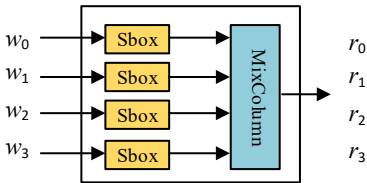
- ▶ S_1, S_2 are 32-to-32 S-transforms



S-transforms in FSM



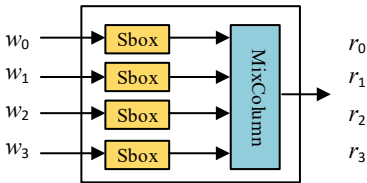
S-transforms in FSM



- $S_1 = L_1 \cdot S_R$, S_R is the AES S-box

$$\begin{pmatrix} r_0 \\ r_1 \\ r_2 \\ r_3 \end{pmatrix} = \begin{pmatrix} x & x+1 & 1 & 1 \\ 1 & x & x+1 & 1 \\ 1 & 1 & x & x+1 \\ x+1 & 1 & 1 & x \end{pmatrix} \cdot \begin{pmatrix} S_R(w_0) \\ S_R(w_1) \\ S_R(w_2) \\ S_R(w_3) \end{pmatrix}$$

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- ▶ $S_2 = L_2 \cdot S_Q$, S_Q is derived from the Dickson polynomials

$$\begin{pmatrix} r_0 \\ r_1 \\ r_2 \\ r_3 \end{pmatrix} = \begin{pmatrix} y & y+1 & 1 & 1 \\ 1 & y & y+1 & 1 \\ 1 & 1 & y & y+1 \\ y+1 & 1 & 1 & y \end{pmatrix} \cdot \begin{pmatrix} S_Q(w_0) \\ S_Q(w_1) \\ S_Q(w_2) \\ S_Q(w_3) \end{pmatrix}$$



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 - ▶ e has distribution D , the SEI (Squared Euclidean Imbalance):

$$\epsilon = |D| \cdot \sum_{e=0}^{|D|-1} \left(D(e) - \frac{1}{|D|} \right)^2$$



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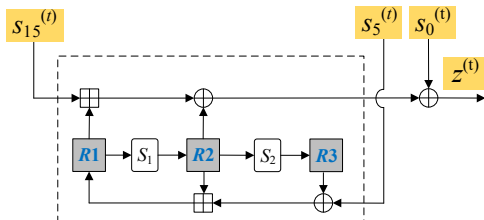
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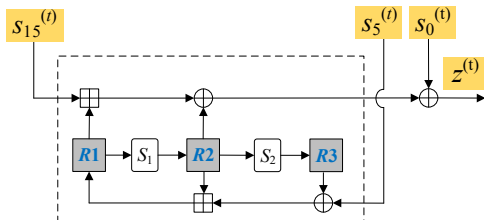
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- ▶ **Key Point:** to find a good approximation with a large bias



Linear Approximation of FSM in SNOW 3G



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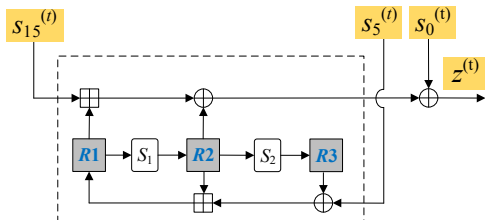


- Explore linear expression including only s_{15}, s_5, s_0, z

$$\bigoplus_{i \in I} (c_z^{(t+i)} z^{(t+i)} \oplus c_{15}^{(t+i)} s_{15}^{(t+i)} \oplus c_5^{(t+i)} s_5^{(t+i)} \oplus c_0^{(t+i)} s_0^{(t+i)})$$

- $c_z^{(t+i)}, c_{15}^{(t+i)}, c_5^{(t+i)}, c_0^{(t+i)}$ are linear masking matrices

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- ▶ $c_z^{(t+i)}, c_{15}^{(t+i)}, c_5^{(t+i)}, c_0^{(t+i)}$ are linear masking matrices
- ▶ The SEI of it evaluates the quality of the approximation
 - ▶ Find good **time set I** and **masking matrices**

Linear Approximation of FSM

Consider 3 consecutive keystream blocks to cancel out R_1, R_2, R_3

Registers update and recursion at three time instances

$$R2^{(t+1)} = L_1 \cdot S_R(R1^{(t)})$$

$$R3^{(t+1)} = L_2 \cdot S_Q(R2^{(t)})$$

$$R1^{(t+1)} = R2^{(t)} \boxplus_{32} (R3^{(t)} \oplus s_5^{(t)})$$

$$R1^{(t-1)} = S_R^{-1} \cdot L_1^{-1}(R2^{(t)})$$

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Keystream symbols at 3 consecutive time instances

$$z^{(t-1)} = (S_R^{-1} L_1^{-1}(R2^{(t)}) \boxplus_{15} s_{15}^{(t-1)}) \oplus (S_Q^{-1} L_2^{-1}(R3^{(t)}) \oplus s_0^{(t-1)})$$

$$z^{(t)} = (R1^{(t)} \boxplus_{15} s_{15}^{(t)}) \oplus R2^{(t)} \oplus s_0^{(t)}$$

$$L_1^{-1} z^{(t+1)} = L_1^{-1}(R2^{(t)} \boxplus_{15} (R3^{(t)} \oplus s_5^{(t)}) \boxplus_{15} s_{15}^{(t+1)}) \oplus S_R(R1^{(t)}) \oplus L_1^{-1} s_0^{(t+1)}$$

L_1^{-1} is the inverse of L_1 , used as a linear masking matrix



24-bit Linear Approximation

Build 24-bit symbols: combining the first bytes

$$\underbrace{\begin{pmatrix} z^{(t-1)} \\ z^{(t)} \\ L_1^{-1} z^{(t+1)} \end{pmatrix}}_{[0,0,0]} \quad \text{Sample at } (t): Z^{(t)}$$

$$= \underbrace{\begin{pmatrix} (S_R^{-1}(L_1^{-1}R2^{(t)}) \boxplus s_{15}^{(t-1)}) \oplus s_{15}^{(t-1)} \oplus S_Q^{-1}(L_2^{-1}R3^{(t)}) \\ R2^{(t)} \\ L_1^{-1}[(R2^{(t)} \boxplus (R3^{(t)} \oplus s_5^{(t)} \boxplus s_{15}^{(t+1)})) \oplus s_5^{(t)} \oplus s_{15}^{(t+1)}] \end{pmatrix}}_{[0,0,0]} \quad \text{24-bit Noise } N2^{(t)}$$

$$\oplus \underbrace{\begin{pmatrix} 0 \\ (R1^{(t)} \boxplus s_{15}^{(t)}) \oplus s_{15}^{(t)} \\ S_R(R1^{(t)}) \end{pmatrix}}_{[0,0,0]} \quad \text{24-bit Noise } N1^{(t)}$$

$$\oplus \underbrace{\begin{pmatrix} s_0^{(t-1)} \oplus s_{15}^{(t-1)} \\ s_{15}^{(t)} \oplus s_0^{(t)} \\ L_1^{-1}[s_0^{(t+1)} \oplus s_5^{(t)} \oplus s_{15}^{(t+1)}] \end{pmatrix}}_{[0,0,0]} \quad \text{Contribution from LFSR } S^{(t)}$$

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► $Z^{(t)} = S^{(t)}, \quad N^{(t)} = N1^{(t)} \oplus N2^{(t)}$



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- ▶ $N1^{(t)}, N2^{(t)}$ independent



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- ▶ $Z^{(t)} = S^{(t)}$, $N^{(t)} = N1^{(t)} \oplus N2^{(t)}$
- ▶ $N1^{(t)}, N2^{(t)}$ independent
 - ▶ $\epsilon(N1^{(t)})$: loop over $R1^{(t)}[0], s_{15}^{(t)}[0]$ in $O(2^{16})$



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 - ▶ How about $\epsilon(N2^{(t)})$? (4 32-bit variables: $R2, R3, s_5, s_{15}$)



Bias Computing of $\epsilon(N2^{(t)})$

Split variables / noise expression into smaller fields [ZXM15]¹[MJ05]²

- ▶ Compute sub-distributions and combine them

¹Zhang B., et al. Fast correlation attacks over extension fields, large-unit...CRYPTO'2015.

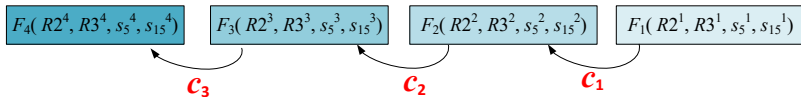
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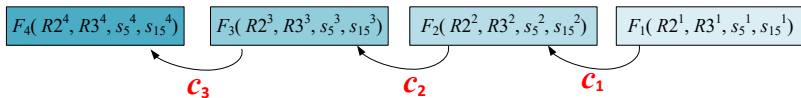
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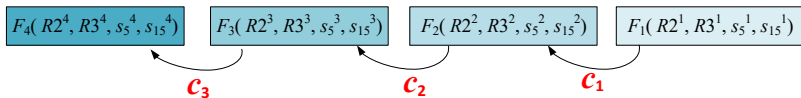
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Split variables / noise expression into smaller fields [ZXM15]¹[MJ05]²

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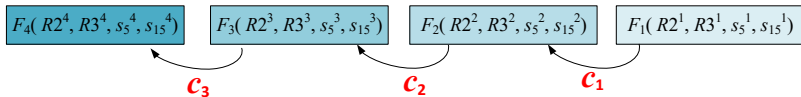
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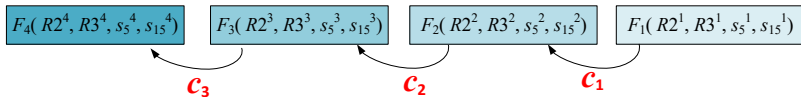
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Q: Is the derived bias correct?

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- ▶ **Decision rule:**

$$P_X = \begin{cases} P_N, & \text{if } D(P_X || P_U) > D(P_X || P_N), \\ P_U, & \text{if } D(P_X || P_U) < D(P_X || P_N). \end{cases}$$

- ▶ $D(x||y)$: **KL divergence (or relative entropy)** between x, y
- ▶ The closer x, y is, the smaller $D(x||y)$ would be



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- ▶ Build random sequences: lower 24 bits of keystream symbols
- ▶ For every sequence, check which distribution it follows
- ▶ Errors:
 - ▶ TYPE I: a noise distribution is judged as random
 - ▶ TYPE II: a random distribution is judged as biased



Results of the Experimental Verification

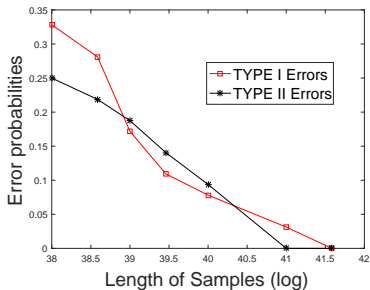


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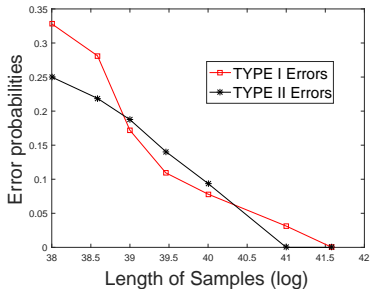


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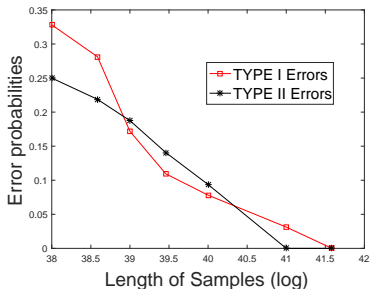


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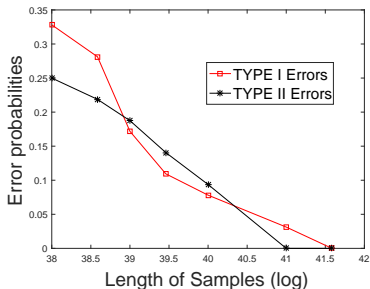


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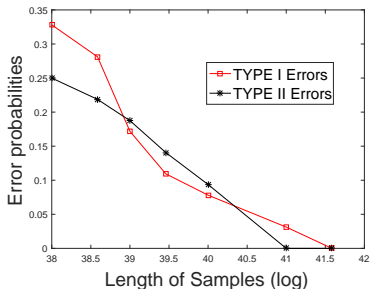


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- ▶ The bias should be correct!



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- ▶ Equivalent to finding a multiple of the generating polynomial $P(x)$ of weight 3, 4, or 5, with all coefficients being 1



Finalize the Distinguishing Attack

- ▶ Find a weight-4 multiple $K(x)$ using method from [LJ14]³
 - ▶ Time and storage complexities $O(2^{172})$

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- ▶ Bias: $\epsilon(X) = \epsilon(4 \times N) > 2^{-163}$ (regarded as independent)
- ▶ Data complexity $O(2^{163})$

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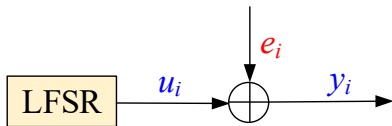
Basics of Correlation Attacks

- ▶ Modeled as decoding problems in $GF(2)$ or $GF(2^n)$



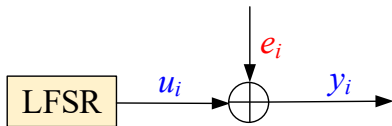
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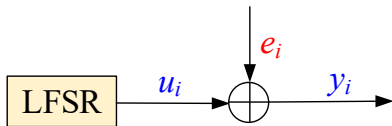


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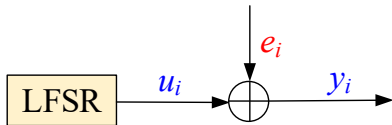
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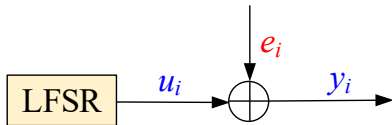
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- ▶ The codeword and received codeword symbols:

$$u_t = (\Lambda(s_0^{(t-1)} \oplus s_{15}^{(t-1)}) \oplus s_0^{(t)} \oplus s_{15}^{(t)} \oplus \Gamma L_1^{-1}[s_0^{(t+1)} \oplus s_5^{(t)} \oplus s_{15}^{(t+1)}])[0]$$

$$y_t = \Lambda z^{(t-1)}[0] \oplus z^{(t)}[0] \oplus \Gamma(L_1^{-1}z^{(t+1)})[0]$$

- ▶ Recover s according to the y sequence
 - ▶ Preprocessing: generating parity checks
 - ▶ Processing: decoding



Finalize the Correlation Attack [ZXM15]⁴

- ▶ Preprocessing: generating parity checks
 - ▶ Generating parity checks involving fewer LFSR states
 - ▶ Requires parity checks $O(2^{171.67})$
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Outline

- ① Motivation
- ② The SNOW 3G Cipher
- ③ Linear Cryptanalysis of SNOW 3G
 - Linear Approximation of FSM
 - Distinguishing Attack
 - Correlation Attack
- ④ Conclusions



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Thank you

Thank you for your attention!

