Meteor From Space

Cryptographically Secure Steganography For Realistic Distributions

Jeremy Boy

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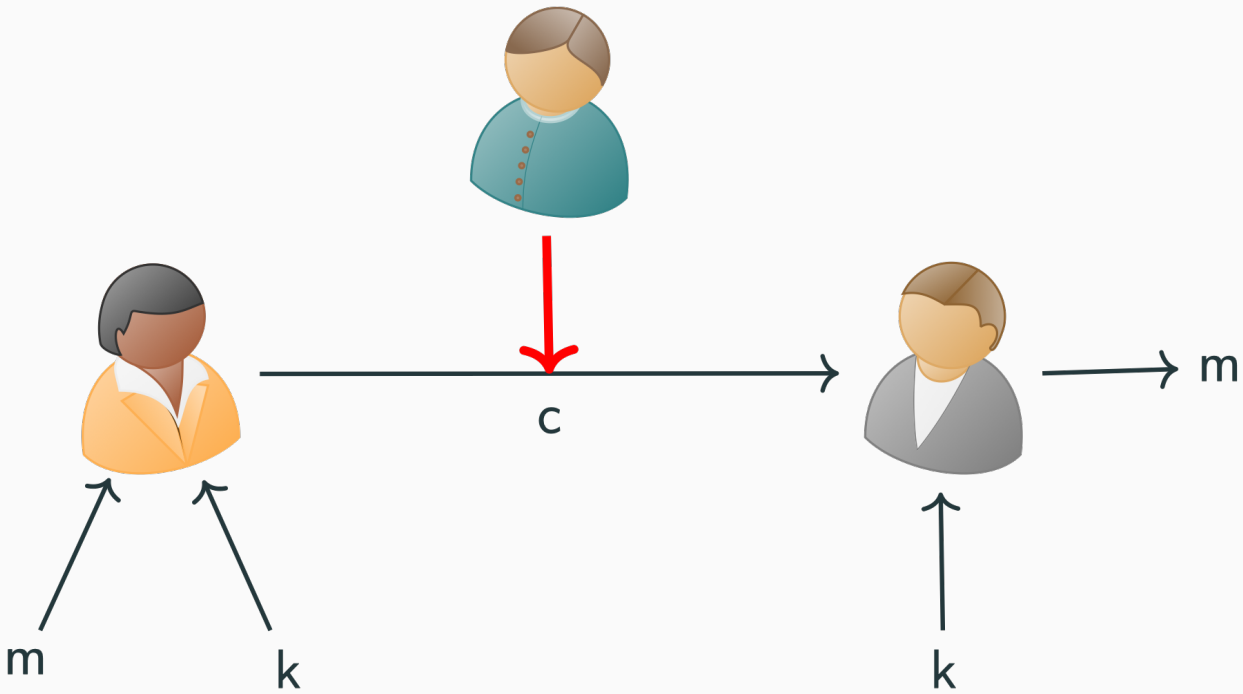
Universitt zu Lbeck

Introduction



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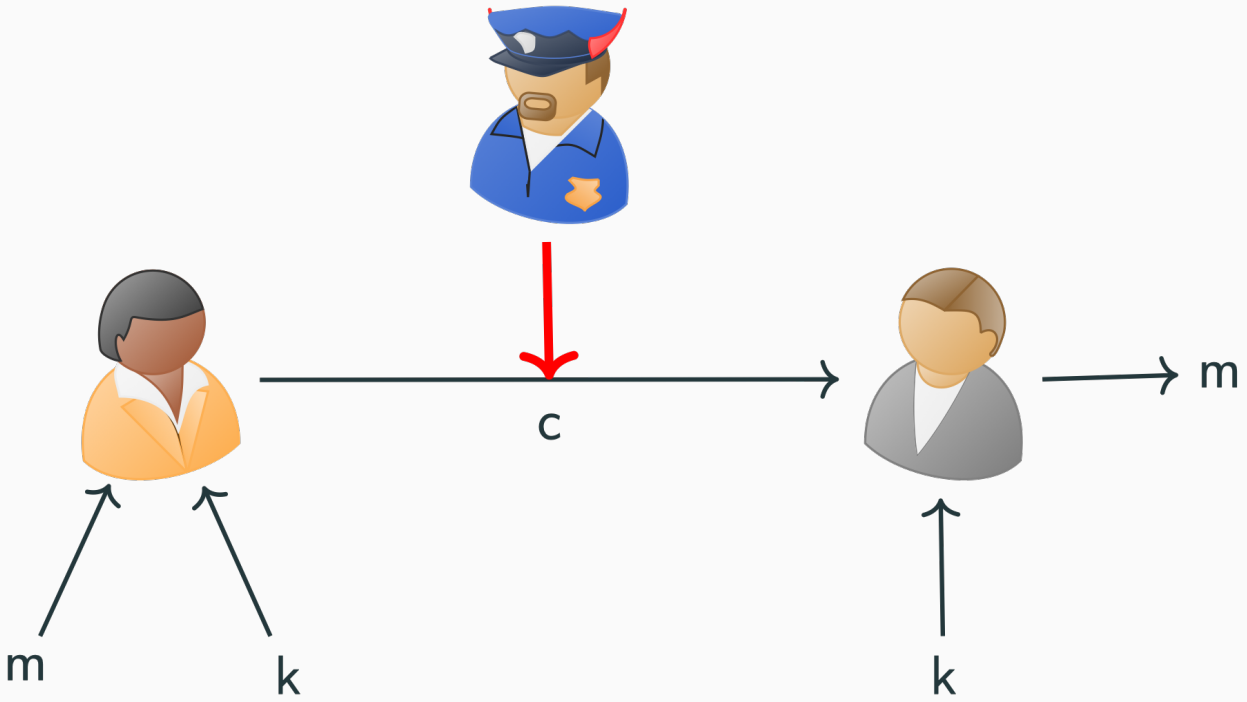

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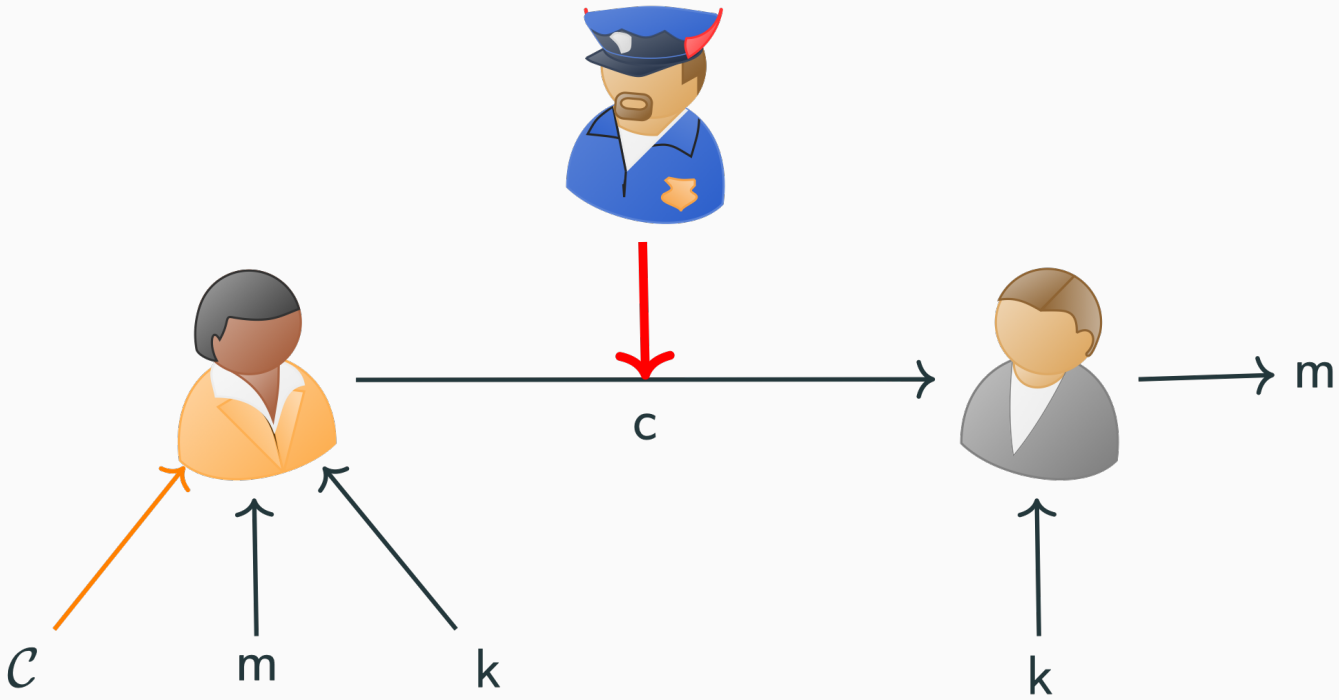

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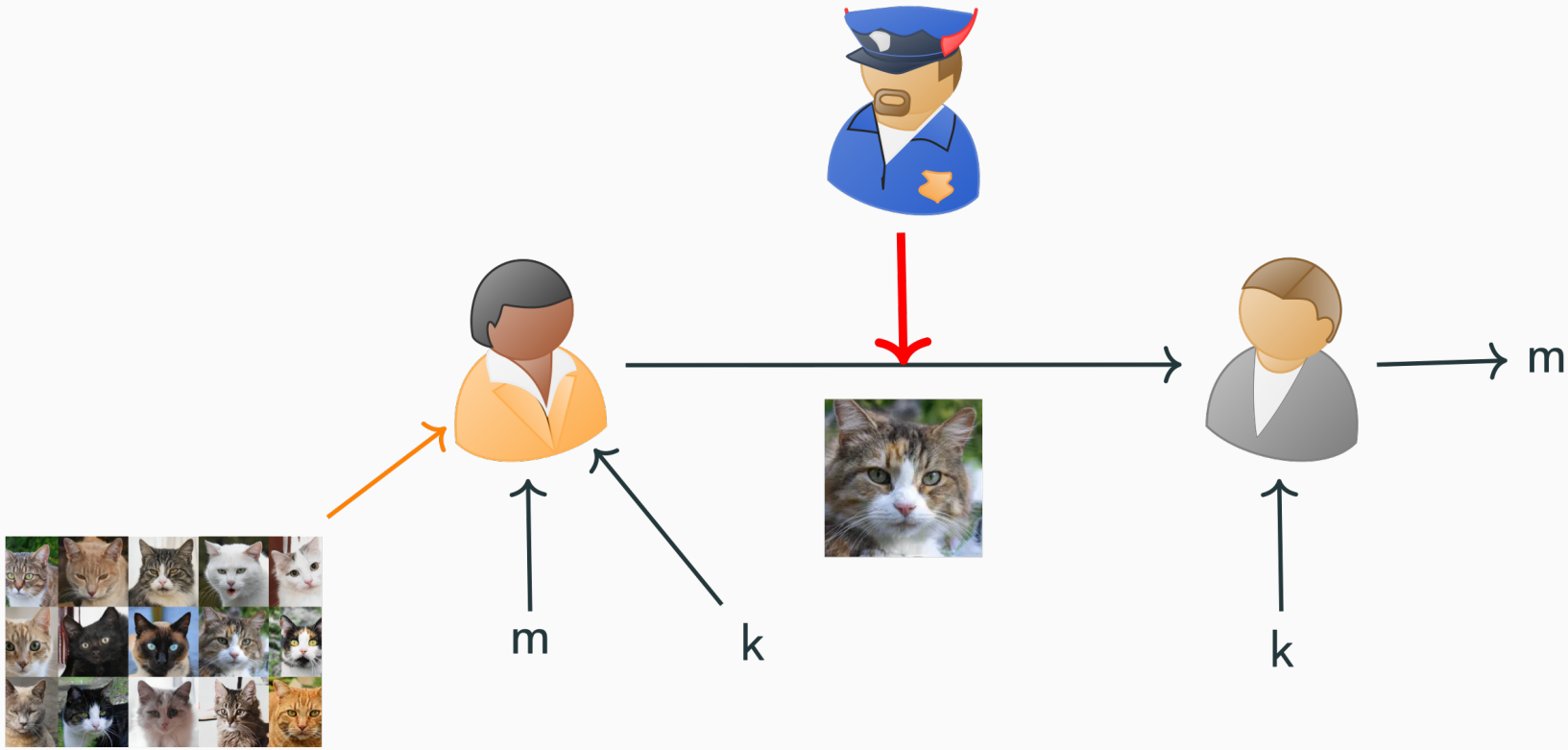

Meteor From Space

1. Overview
2. Generative Neural Networks
3. Ranged Randomness Recoverable Sampling Scheme (RRRSS)
4. From RRRSS To Stegosystem
5. Security And Performance
6. Live Demo
7. Conclusion

Overview

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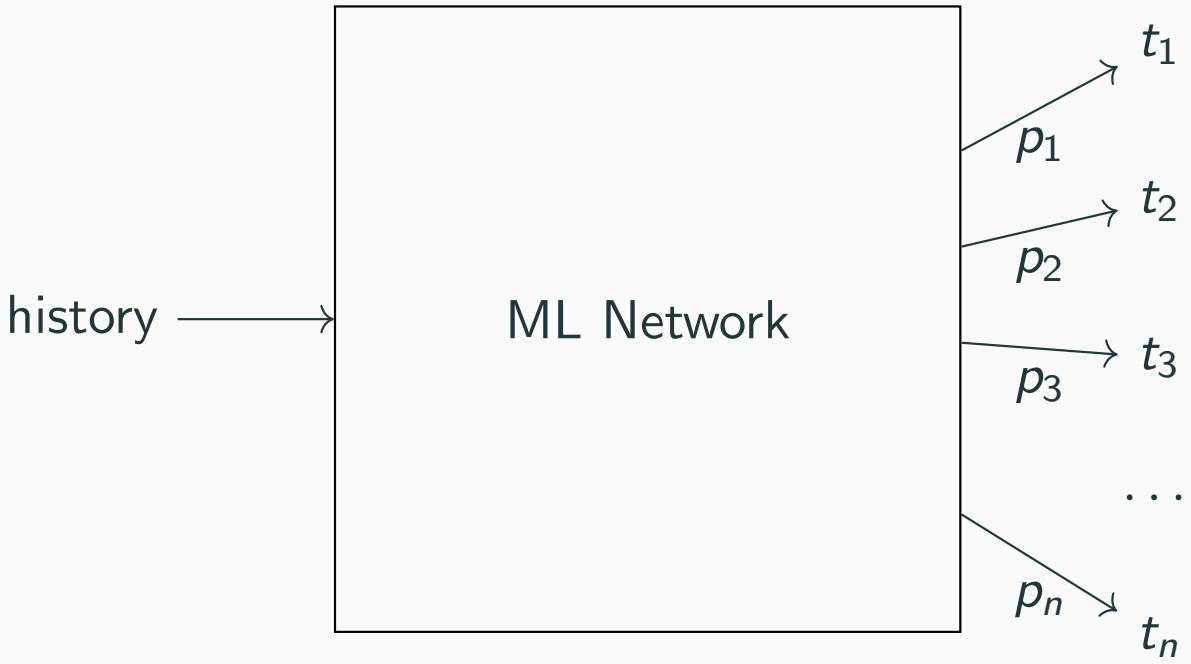
- Use *generative approximation* of natural language to hide information
- Encrypt hiddentext m using pre-shared key k to get ciphertext r
- Alice: manipulate sampling from $\mathcal{C}$ using r to create stegotext s
- Bob: recover r from s and decrypt m using k

Generative Neural Networks

Generative Neural Networks



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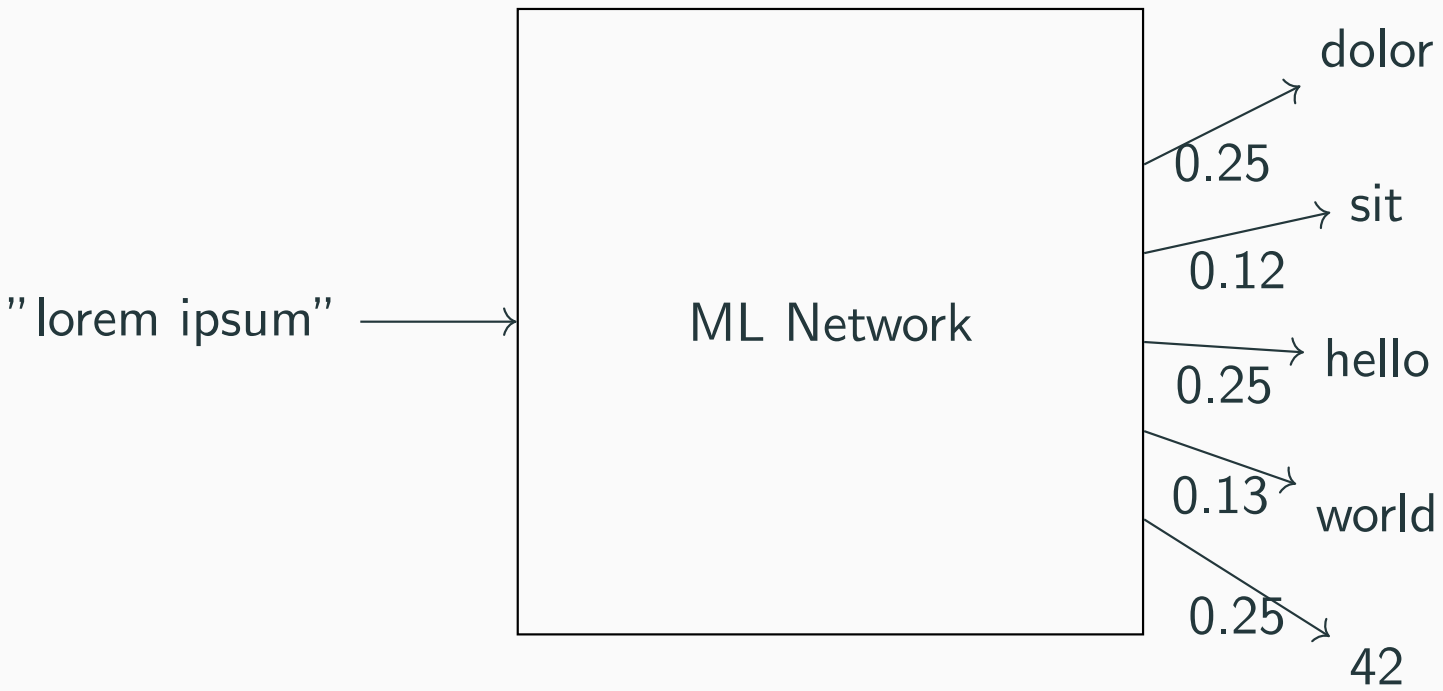

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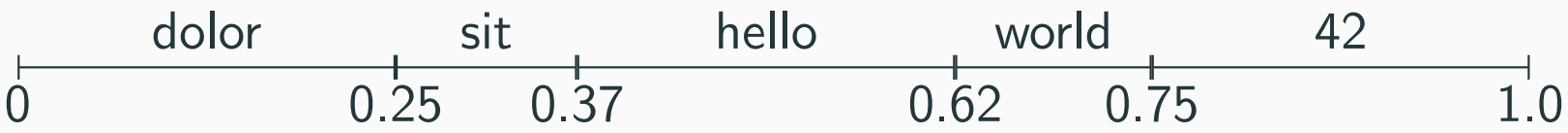

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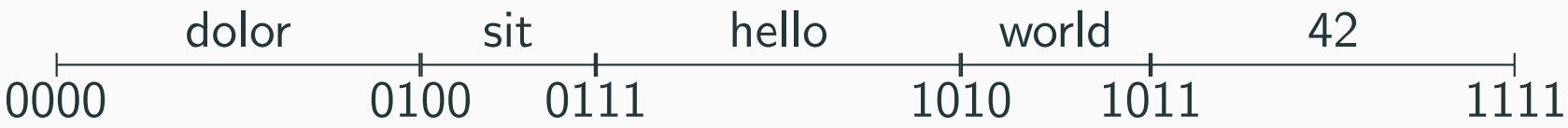

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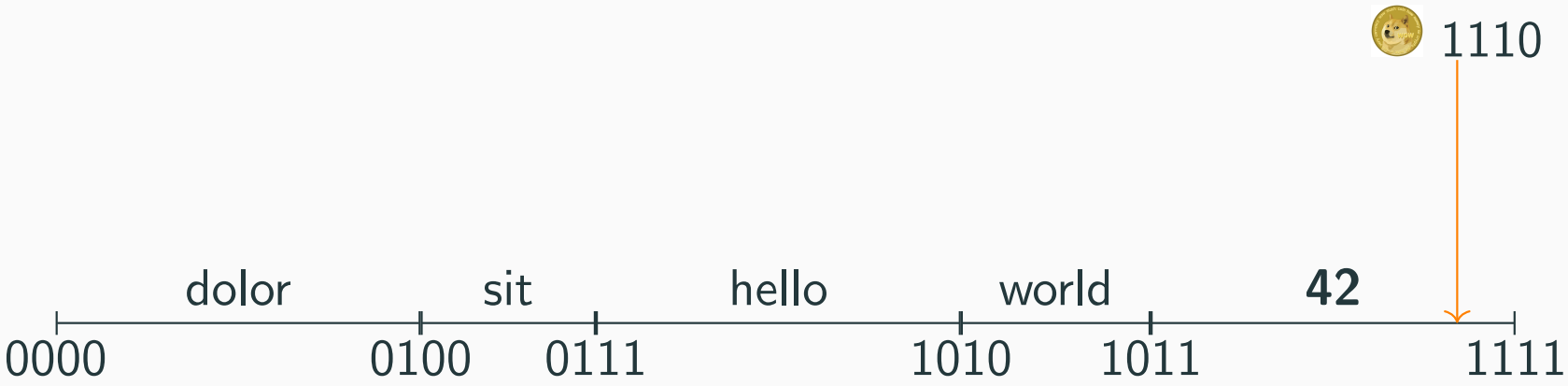

Ranged Randomness Recoverable Sampling Scheme (RRRSS)

Ranged Randomness Recoverable Sampling Scheme

- Let $\mathcal{D}$ be a probability distribution and $\beta \in \mathbb{N}$

$\mathcal{R} := \{r \in \{0,1\}^{\beta} \mid \mathsf{Sample}^{\beta}_{\mathcal{D}}(\mathcal{H}, r) = s\}$

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  2. $\text{Recover}^{\beta}_{\mathcal{D}}(\mathcal{H}, s) \to \mathcal{R}$. On history $\mathcal{H}$ and sample s, output the set $\mathcal{R}$ of possible values for r

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Ranged Randomness Recoverable Sampling Scheme

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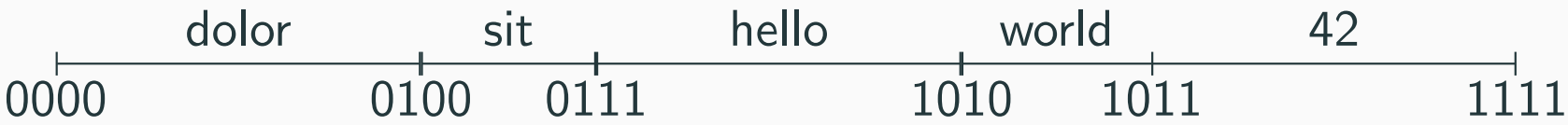

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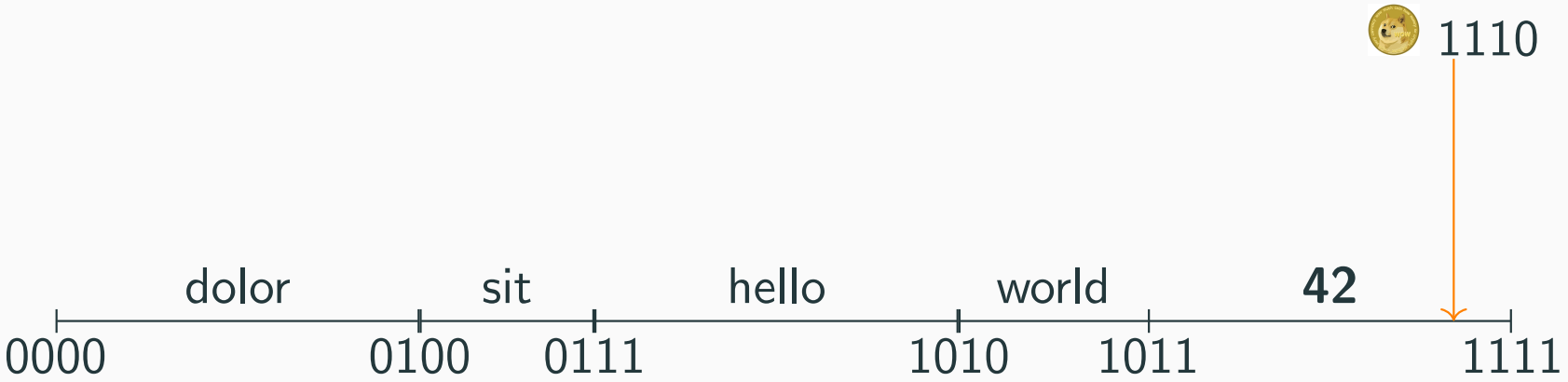

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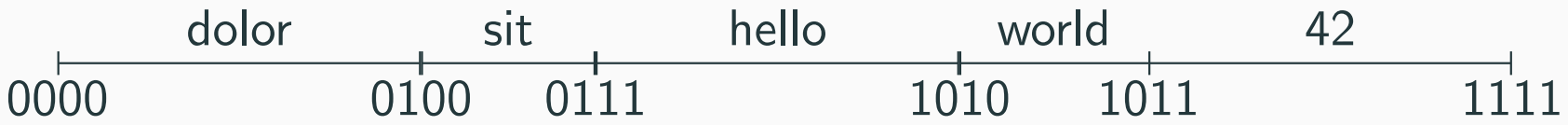

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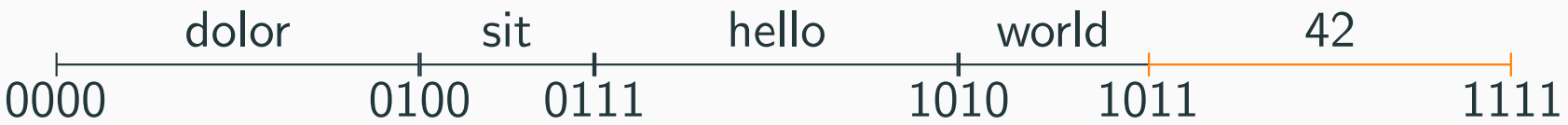

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- Decrypt m from recovered bits using k

From RRRSS To Stegosystem

Algorithm 5: $\text{Encode}^{\beta}_{\mathcal{M}}$

Input: Key k_{prg}, Plaintext Message m, History $\mathcal{H}$
Output: Stegotext Message c

$c \leftarrow \varepsilon, n \leftarrow 0$
while $n < |m|$ **do**
  $mask \leftarrow \text{PRG.Next}(k_{prg})$
  $r \leftarrow m[n : n + \beta] \oplus mask$
  $c_i \leftarrow \text{Sample}^{\beta}_{\mathcal{M}}(\mathcal{H}, r)$
  $\mathcal{R} \leftarrow \text{Recover}^{\beta}_{\mathcal{M}}(\mathcal{H}, c_i)$
  $n_i \leftarrow \text{LenPrefix}^{\beta}(\mathcal{R})$
  $c \leftarrow c \| c_i, n \leftarrow n + n_i, \mathcal{H} \leftarrow \mathcal{H} \| c_i$
Output c

From RRRSS To Stegosystem

Algorithm 6: $\text{Decode}^{\beta}_{\mathcal{M}}$

Input: Key k_{prg}, Stegotext Message c, History $\mathcal{H}$
Output: Plaintext Message m

$x \leftarrow \varepsilon$
Parse c as $\{c_0, c_1, \ldots, c_{|c|-1}\}$
for $i \in \{0, 1, \ldots, |c| - 1\}$ **do**
    $\mathcal{R} \leftarrow \text{Recover}^{\beta}_{\mathcal{M}}(\mathcal{H}, c_i)$
    $x_i \leftarrow \text{Prefix}^{\beta}(\mathcal{R})$
    $mask \leftarrow \text{PRG.Next}(k_{prg})$
    $x \leftarrow x \| (x_i \oplus mask[0 : |x_i|])$
    $\mathcal{H} \leftarrow \mathcal{H} \| c_i$
Output x

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Live Demo

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- We can achieve competitive performance using symmetric encryption