Deep Learning-Based Differential Distinguishers for Cryptographic Sequences

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INDOCRYPT 2024, CHENNAI, Tamil Nadu, India

December 2024

Outline

- Introduction
- A Brief History
- Deep Learning for Sequence Classification
- Neural Distinguishers based on Sequence Classification
- Results and Observation
- Conclusion

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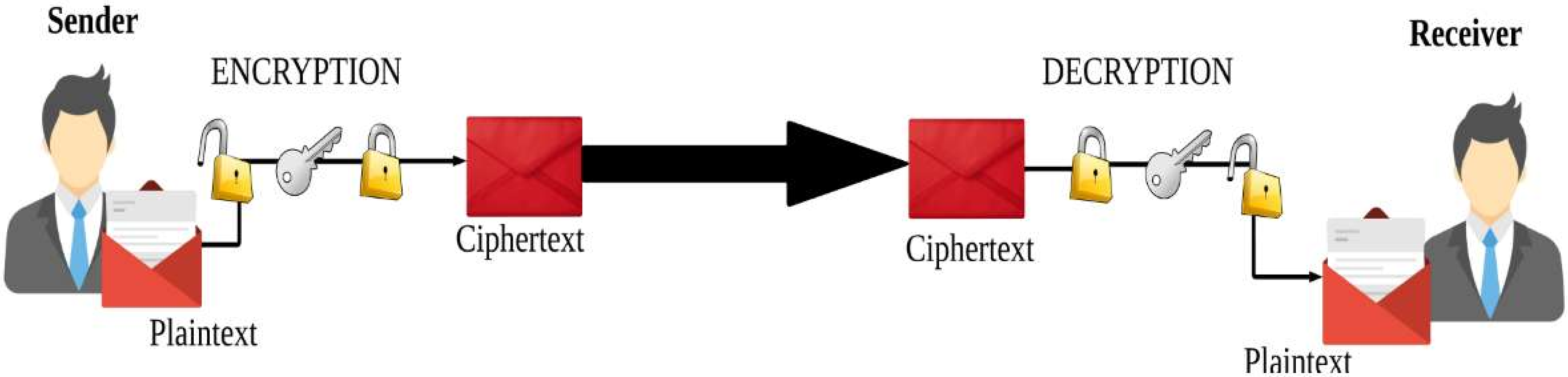

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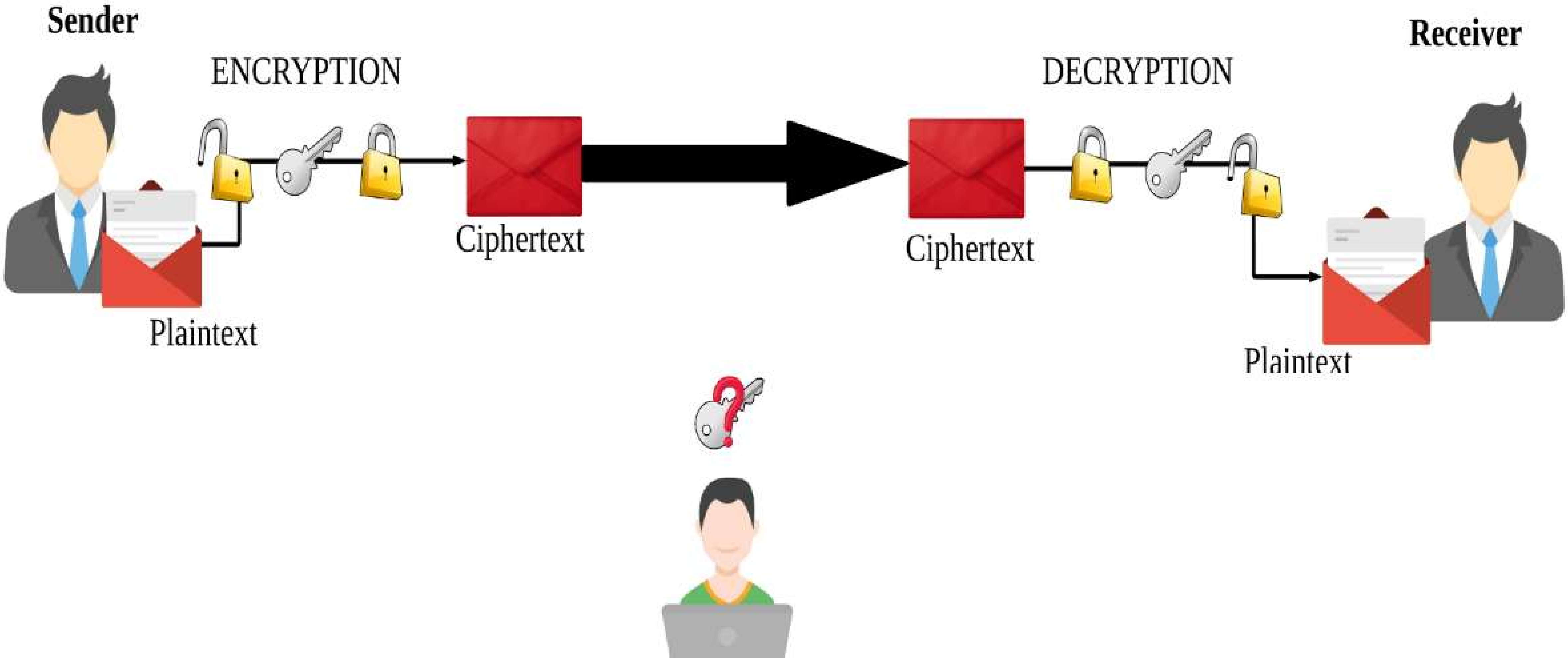

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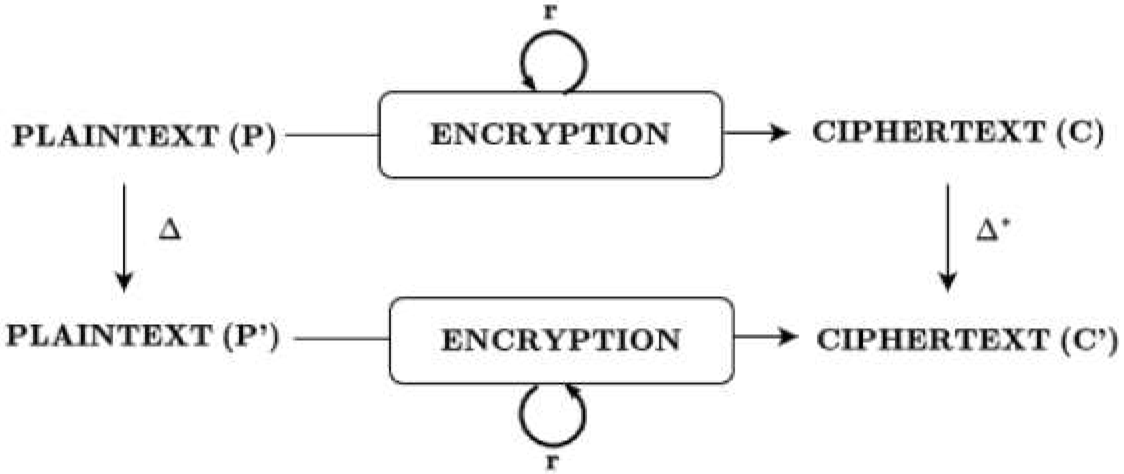
- Differential Cryptanalysis:



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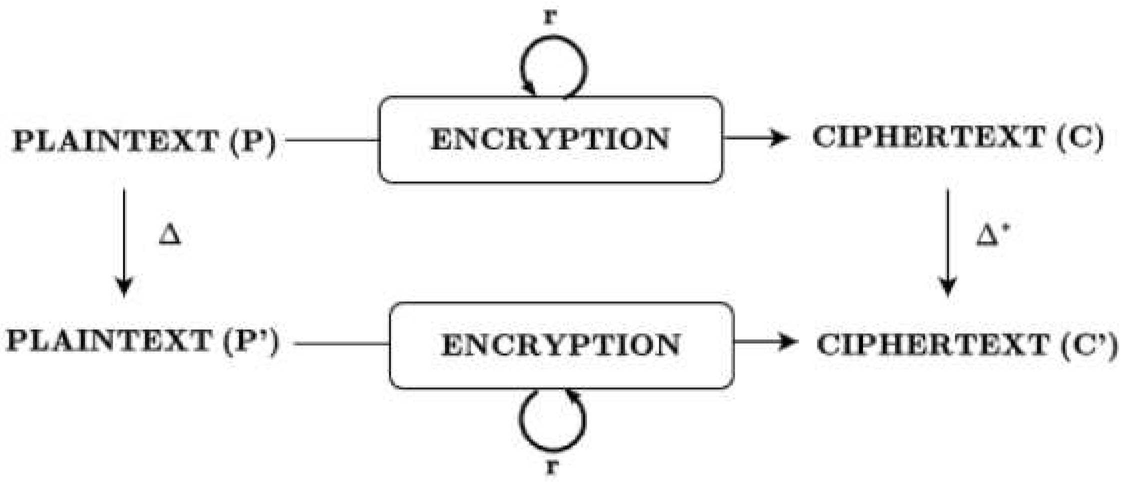

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  relies on Difference Distribution Table (DDT)

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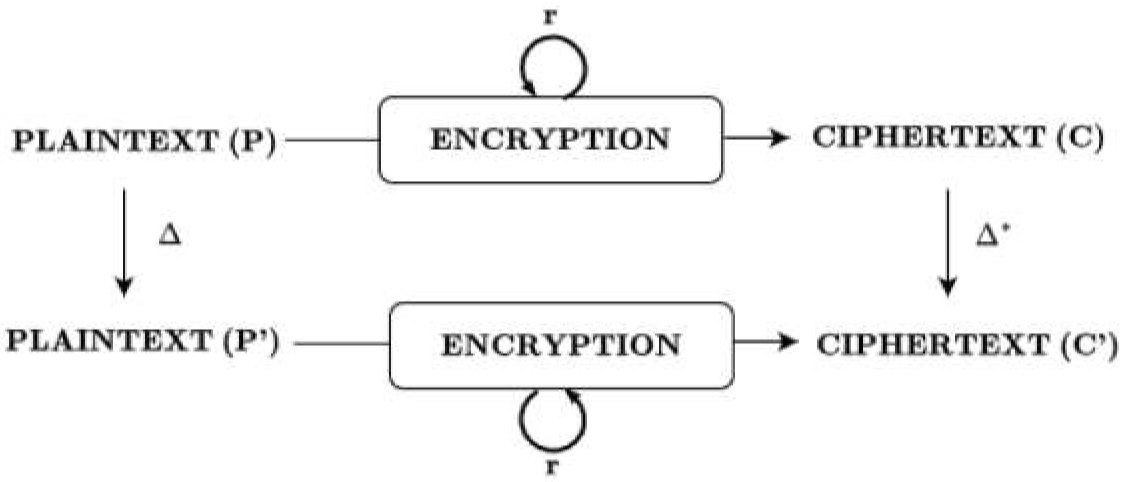
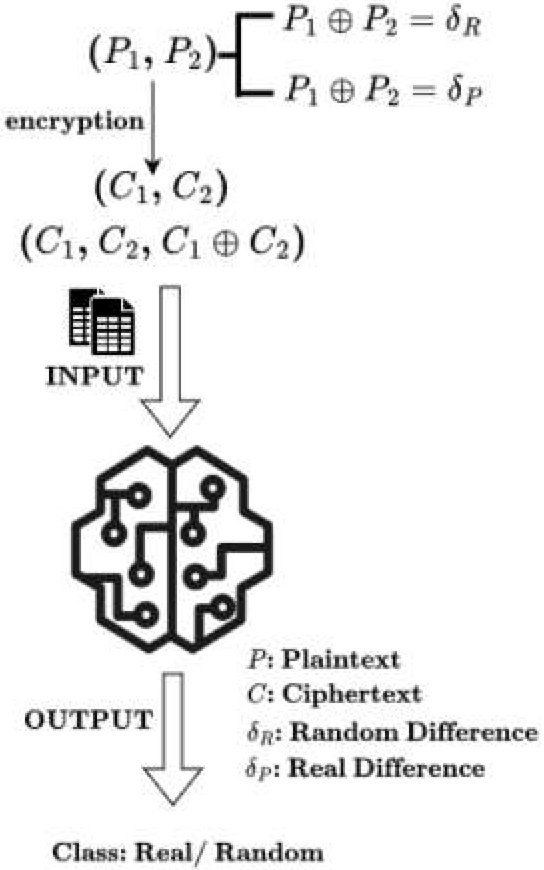


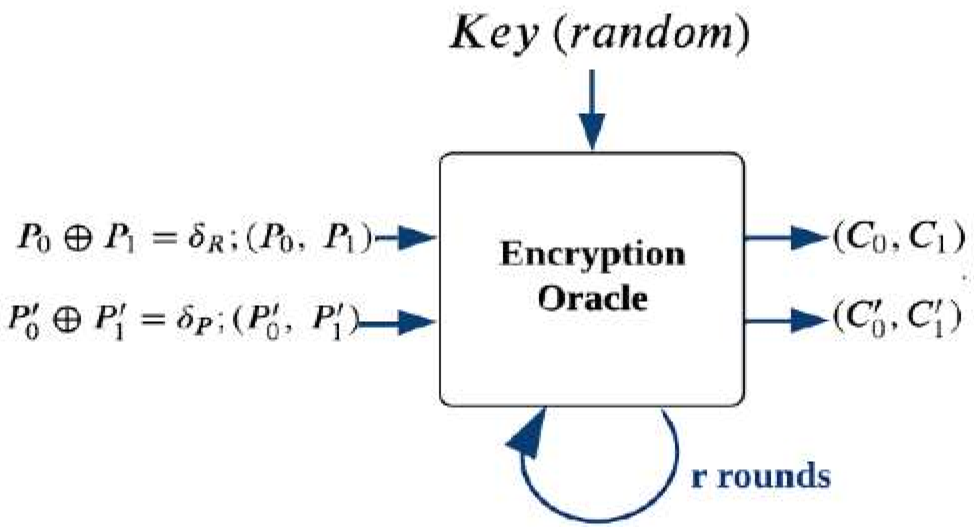


- Conventional Method →
  relies on Difference Distribution Table (DDT)

- New Research Direction → utilize deep learning model
  to get a distinguisher [Aron Gohr]

Introduction

- Deep Learning-based Distinguisher



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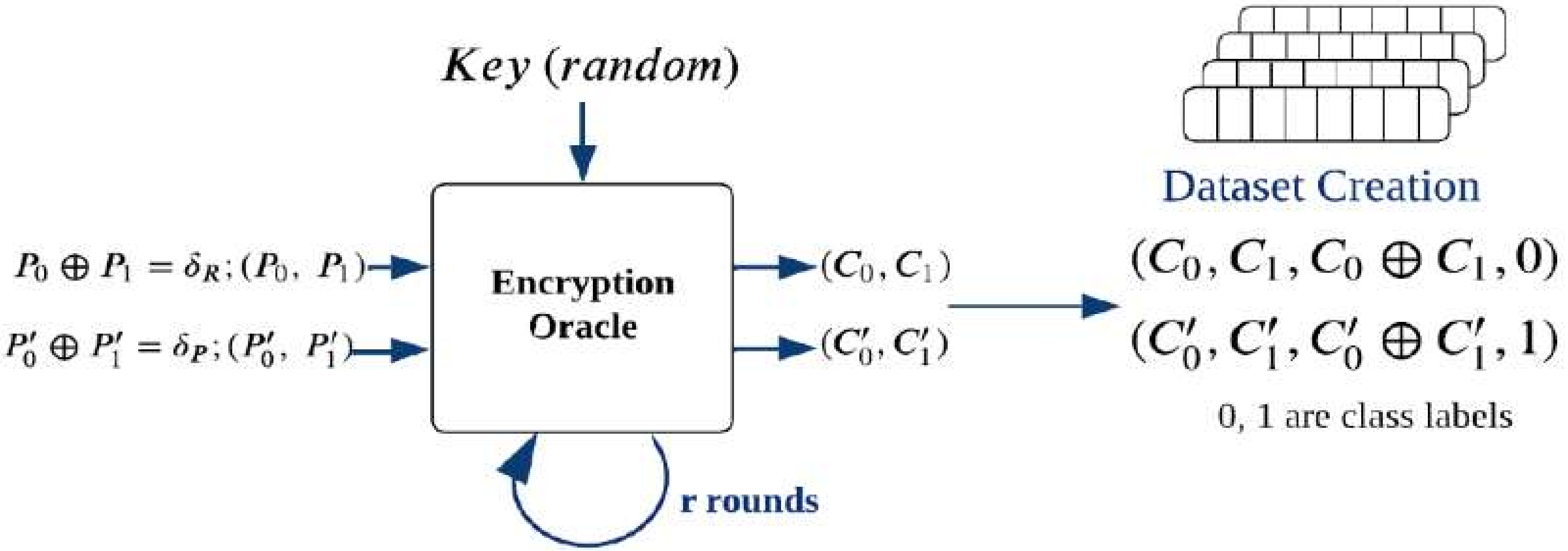

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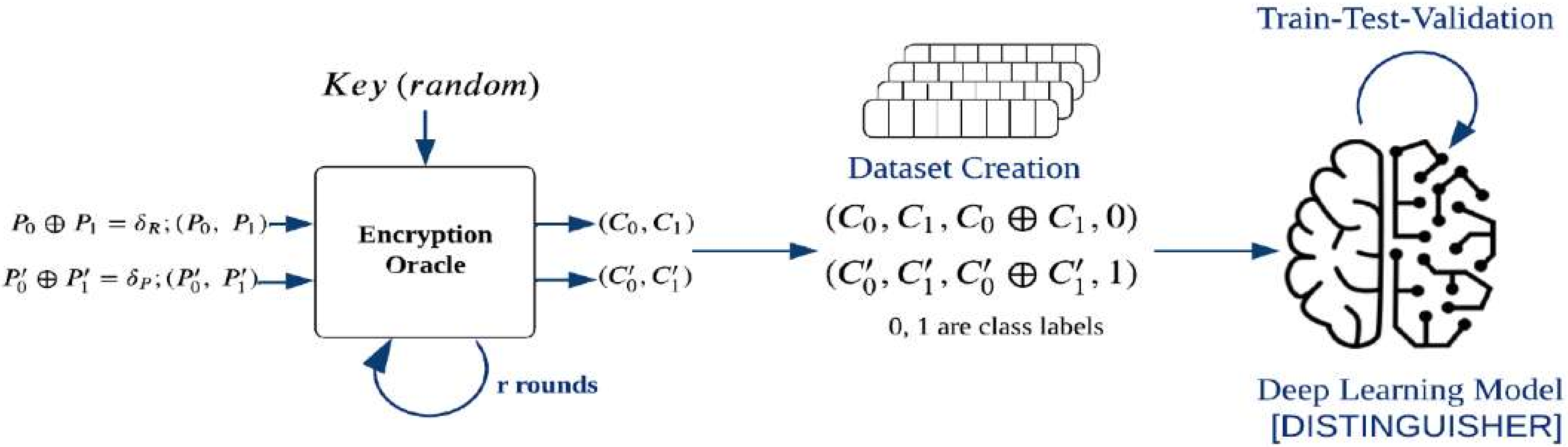

What is the purpose of a good distinguisher?

- a distinguisher can highlight whether an encryption scheme deviates from the expected random behavior
- some subtle patterns that may go unnoticed otherwise can be captured by an automated approach
- a good distinguisher is a prerequisite for a successful key recovery attack

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A Brief History

1. Aron Gohr proposed distinguisher for *SPECK* [*ResNet*]
2. Zhang et al. proposed distinguisher for *TweGIFT-128* [*MLP*]
3. Wang et al. obtained distinguishers for *SPECK32/64* and *PRESENT64/80* [*Adaboost, DT, KNN, Logistic Regression, RFC, SVM, MLP, CNN, RNN, LSTM*]
4. Baksi et al. presented the notion of multiple input differences to define neural distinguishers [*MLP, CNN, LSTM*]
5. Mishra et al. proposed distinguisher for *GIFT64* and *PRIDE* [*MLP, CNN*]
6. Bacuieti et al. proposed using *Convolutional Autoencoders* as preprocessors before training the model.
7. Liu et al. obtained improved accuracy for *SPECK* [*CNN*]
8. Deng et al. obtained improved results for *SPECK* [*Attention+CNN*]
9. Bellini et al. proposed a *DBitNet* network [*CNN based*]
10. Shen et al. proposed a score distribution based technique [*MLP*]

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Deep Learning for Sequence Classification

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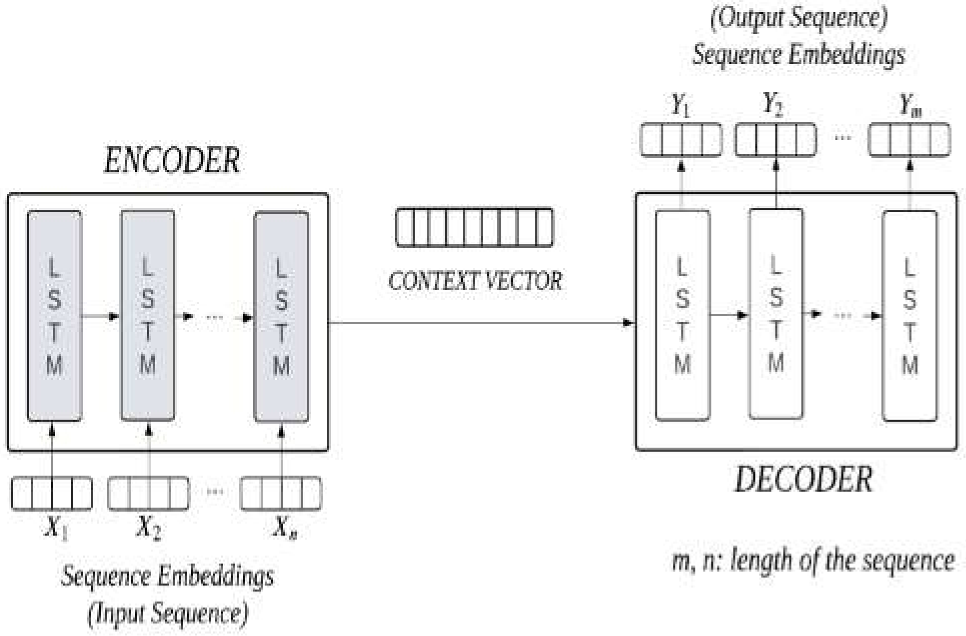
e.g., for a 64−bit blocksize cipher : [28, 121, 9, 250, 30, 66, 12, 97]

Sequence Detection Models

- Encoder-Decoder Network: proposed in 2014, a team led by Ilya Sutskever from Google



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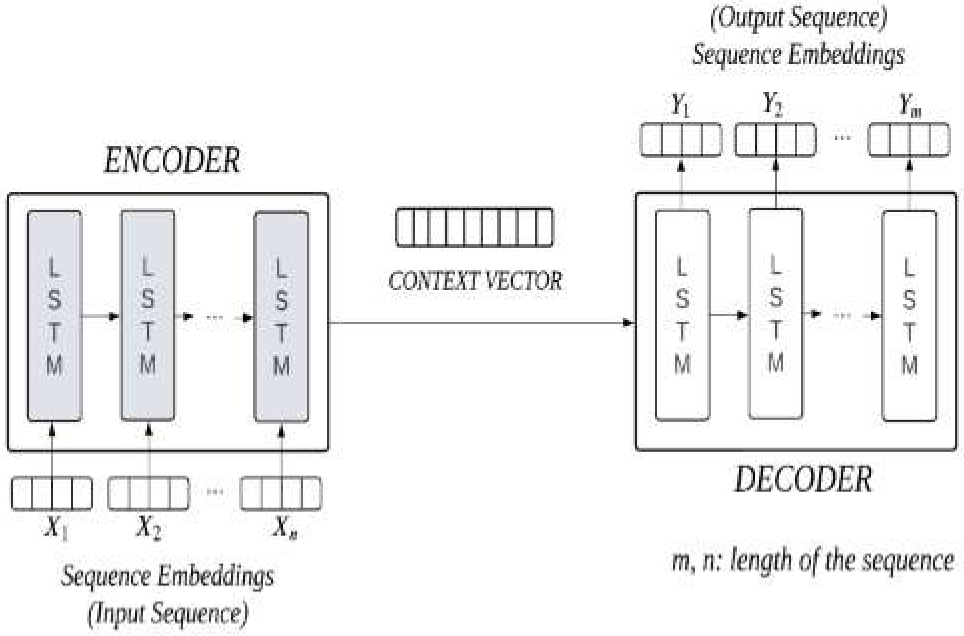
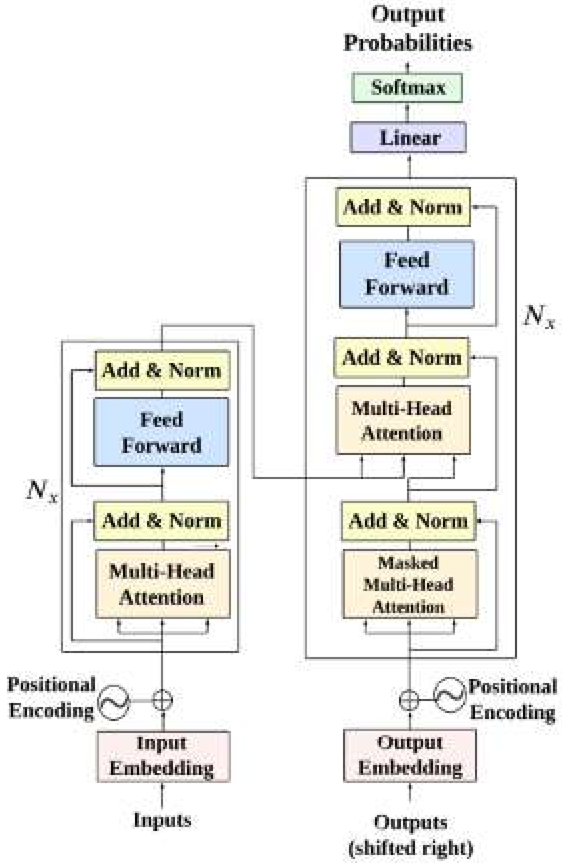


- Transformer: published in 2017 by Google Brain titled "Attention is all you need"



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The Neural Distinguisher Pipeline

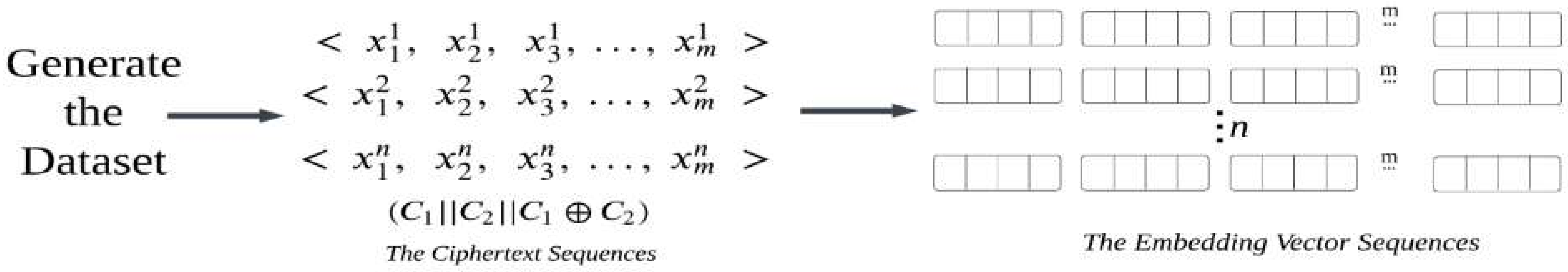
Generate the Dataset →

$$< x_1^1,\ x_2^1,\ x_3^1,\ \ldots,\ x_m^1 >$$
$$< x_1^2,\ x_2^2,\ x_3^2,\ \ldots,\ x_m^2 >$$
$$< x_1^n,\ x_2^n,\ x_3^n,\ \ldots,\ x_m^n >$$

$(C_1 || C_2 || C_1 \oplus C_2)$

The Ciphertext Sequences

The Neural Distinguisher Pipeline



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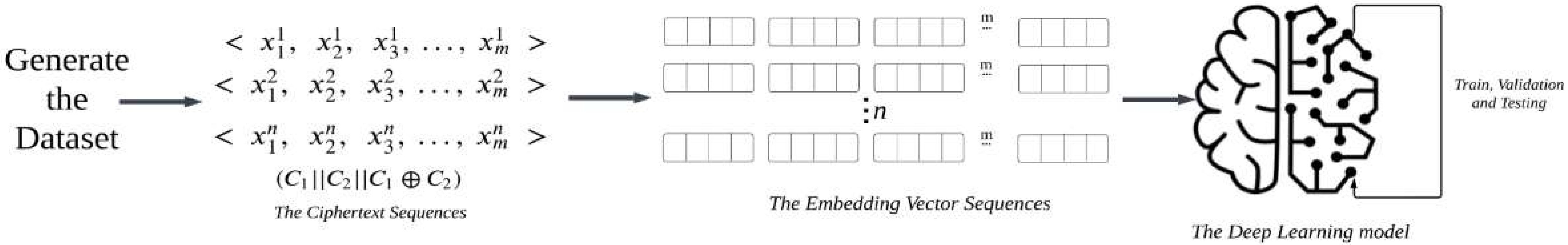

Data Generation

The Algorithm used for creating dataset:

Algorithm 1 Data Generation Algorithm: Differential Distinguisher

Input: Plaintext difference, δ_P; number of encryption rounds, r; Dataset size, $\mathcal{N}$

Output: Dataset, $\mathcal{D}$

$\mathcal{D} \leftarrow \emptyset$
for $i = 1$ to $\mathcal{N}$ **do**
    $\mathcal{K} \leftarrow RANDOM\_BYTES()$ ▷ generating random key, $\mathcal{K}$
    $\mathcal{P}_1 \leftarrow RANDOM\_BYTES()$ ▷ generating random plaintext, $\mathcal{P}$
    $\mathcal{C}_1 \leftarrow ENCRYPT(\mathcal{P}_1, \mathcal{K}, r)$ ▷ call the encryption oracle, returns ciphertext, $\mathcal{C}$
    $choice \leftarrow random\_number(0, 1)$
    if $(choice = 0)$ **then** ▷ random difference
        $\mathcal{P}_2 \leftarrow RANDOM\_BYTES()$
        $Label \leftarrow 0$
    else ▷ real difference
        $\mathcal{P}_2 = \mathcal{P}_1 \oplus \delta_{\mathcal{P}}$
        $Label \leftarrow 1$
    end if
    $\mathcal{C}_2 \leftarrow ENCRYPT(\mathcal{P}_2, \mathcal{K}, r)$
    $\mathcal{C}_{XOR} \leftarrow \mathcal{C}_1 \oplus \mathcal{C}_2$
    $\mathcal{D} \leftarrow \mathcal{D} \cup (\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_{XOR}, Label)$ ▷ include in the dataset
end for
return $\mathcal{D}$

Deep Learning Models

- *LSTM-based Encoder Classifier (LbEC)*

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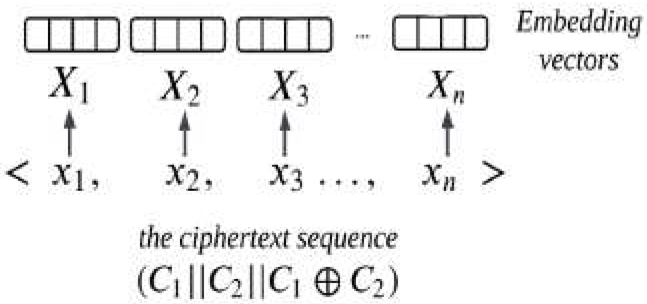

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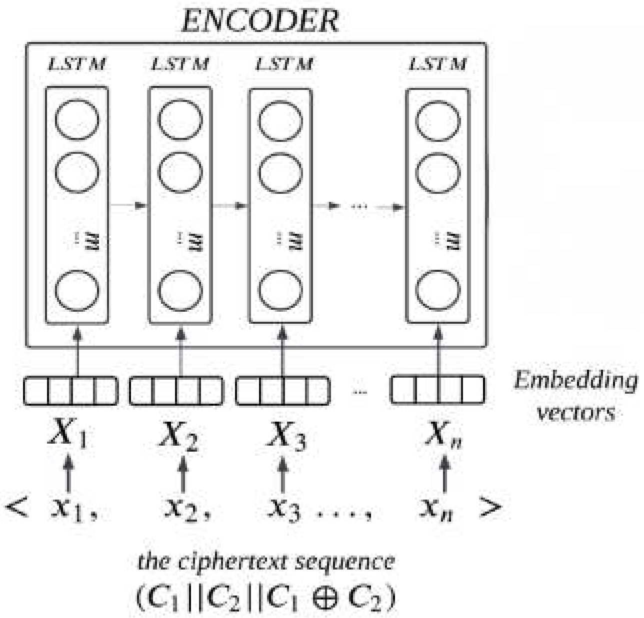

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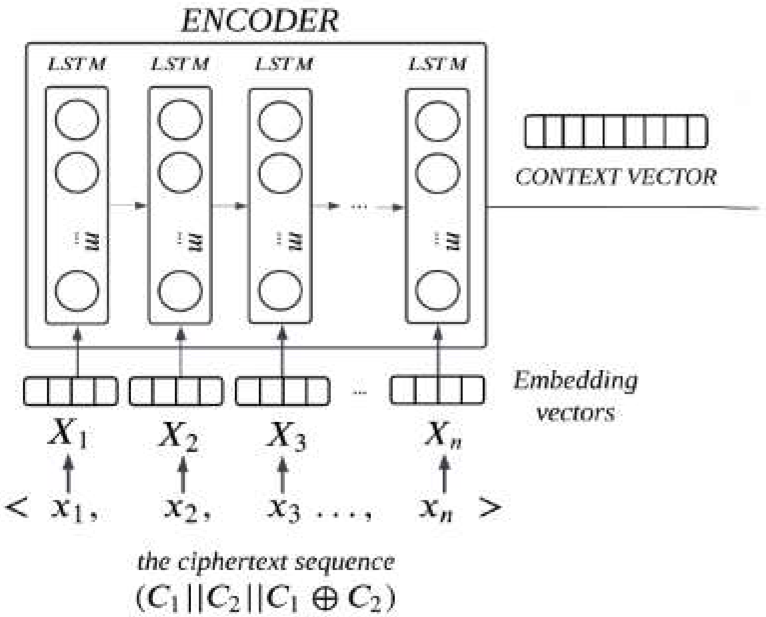

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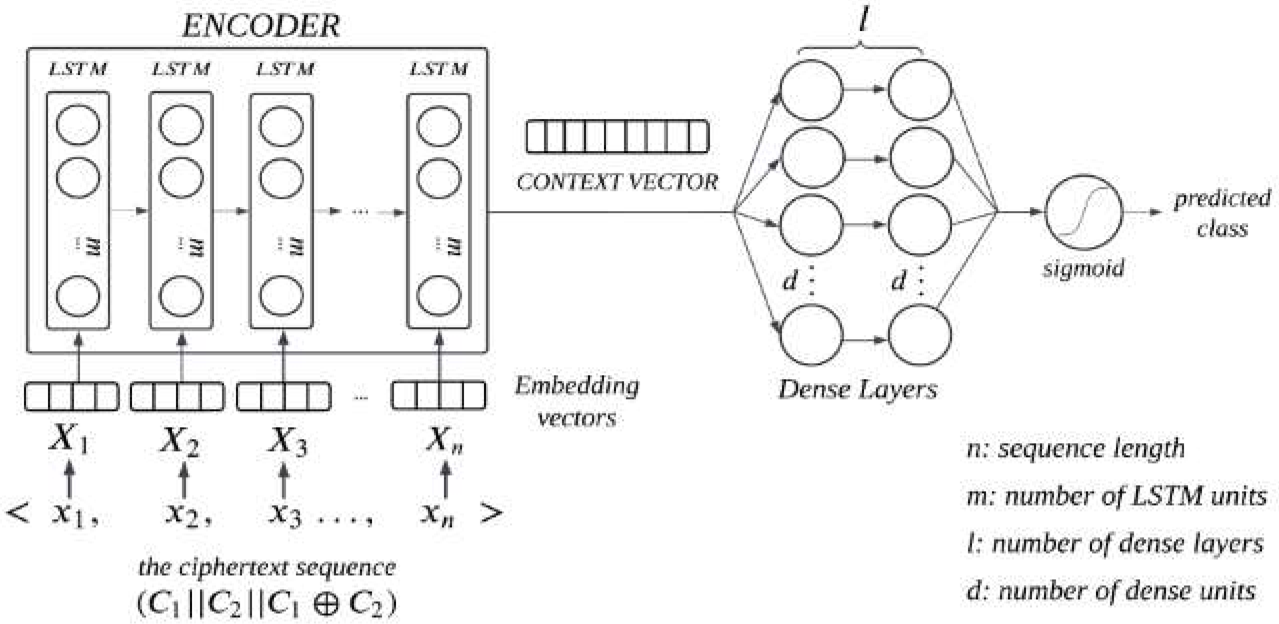

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- *Transformer based Encoder-only Classifier (TbEC)*

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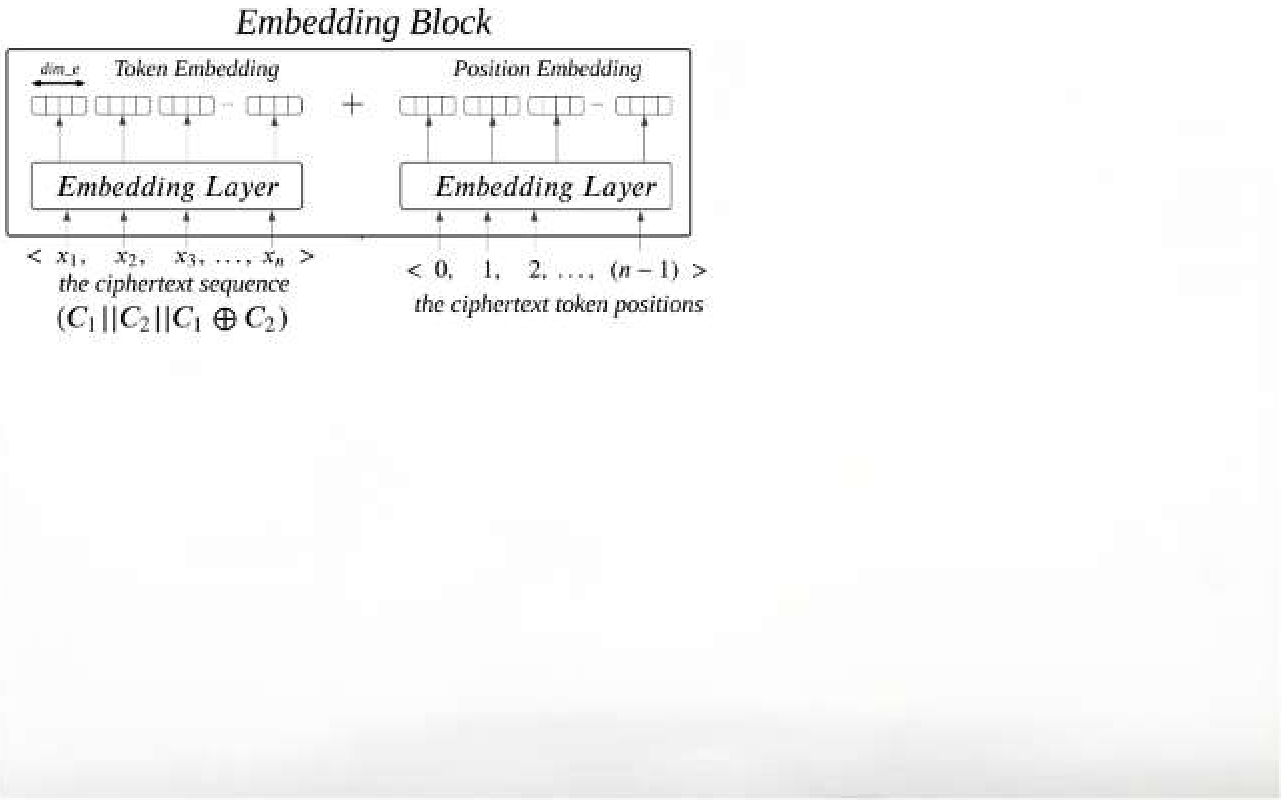

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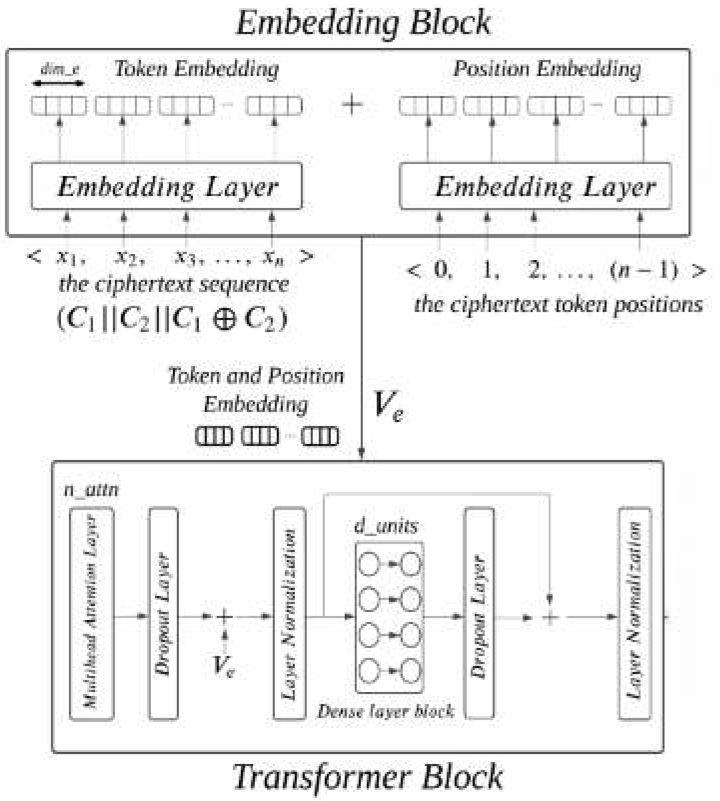

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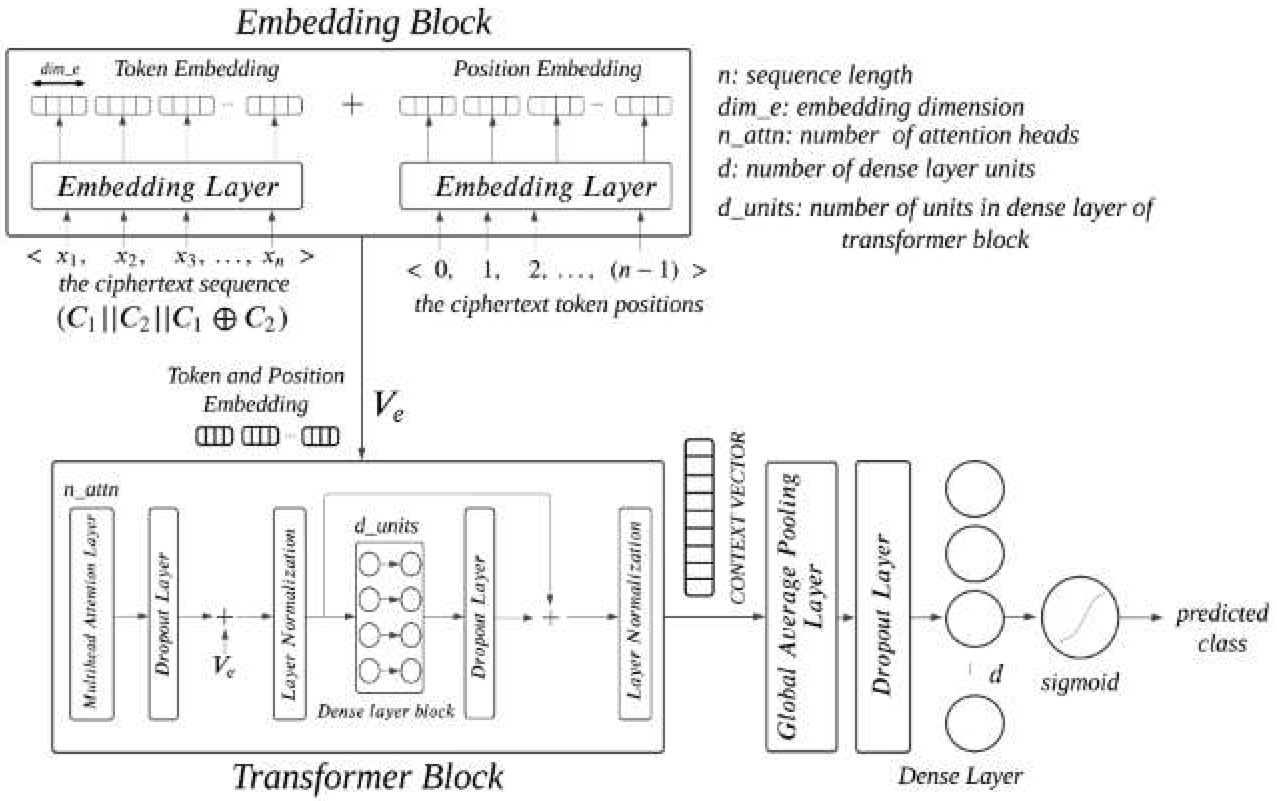

Searching the Distinguisher

The Algorithm used for Searching the Distinguisher

Algorithm 2 Distinguisher Search

Input: Dataset, $\mathcal{D}$

Output: Distinguisher found/ not found

$\mathcal{D}_{train}, \mathcal{D}_{val}, \mathcal{D}_{test} \leftarrow SPLIT\_DATASET(\mathcal{D})$ ▷ split the dataset, $\mathcal{D}$ into train, validation & test sets
$model \leftarrow DEFINE\_MODEL()$ ▷ calls the function definition of the model
$Accuracy_{(train)} \leftarrow TRAIN(model, \mathcal{D}_{train}, \mathcal{D}_{val})$ ▷ train the $model$ on D_{train} & D_{val}
if $Accuracy_{(train)} > 50\%$ **then**
    $Accuracy_{(test)} \leftarrow TEST(model, \mathcal{D}_{test})$ ▷ test the $model$ on D_{test}
    if $Accuracy_{(test)} > 50\%$ **then**
        return "Distinguisher Found"
    else
        return "Distinguisher Not Found"
    end if
else
    return "Distinguisher Not Found"
end if

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Brief Overview of the Ciphers

HIGHT

- *ARX* based, Generalized Fiestel Structure
- block size → 64 bits
- key size → 128 bits
- number of rounds → 32

PRESENT

- *SPN* based
- block size → 64 bits
- key size → 80 bits
- number of rounds → 31

LEA

- *ARX*-based
- block size → 128 bits
- key size → 128 bits
- number of rounds → 24

SPARX

- *ARX* based
- block size → 64 bits
- key size → 128 bits
- number of rounds → 24

Piccolo-80

- *GFN* based
- block size → 64 bits
- key size → 80 bits
- number of rounds → 25

Obtained Results

HIGHT

- $LbEC \to 16$ rounds distinguisher (Accuracy $= 50.02\%$)
- $TbEC \to 11$ rounds distinguisher (Accuracy $= 50.18\%$)

PRESENT

- $LbEC \to 12$ rounds distinguisher (Accuracy $= 50.14\%$)
- $TbEC \to 12$ rounds distinguisher (Accuracy $= 50.01\%$)

LEA

- $LbEC \to 11$ rounds distinguisher (Accuracy $= 50.15\%$)
- $TbEC \to 13$ rounds distinguisher (Accuracy $= 50.12\%$)

SPARX

- $LbEC \to 6$ rounds distinguisher (Accuracy $= 50.62\%$)
- $TbEC \to 6$ rounds distinguisher (Accuracy $= 50.18\%$)

Piccolo-80

- $LbEC \to 6$ rounds distinguisher (Accuracy $= 50.18\%$)
- $TbEC \to 9$ rounds distinguisher (Accuracy $= 50.05\%$)

Comparisons of the Result

Block cipher	Model Architecture	Rounds	Test Accuracy
HIGHT	LGBM[1]	10	50.01%
	CNN[1]	10	50.30%
	LSTM[1]	8	66.36%
	DBitNet[2]	10	75.10%
	LbEC	**16**	**50.02%**
	TbEC	**11**	**50.18%**
PRESENT	CNN based[3]	7	72.05%
	DBitNet[2]	9	50.90%
	LbEC	**12**	**50.14%**
	TbEC	**12**	**50.01%**
LEA	LGBM[1]	9	50.18%
	CNN[1]	9	50.45%
	LSTM[1]	8	59.81%
	DBitNet[2]	11	51.10%
	LbEC	**11**	**50.15%**
	TbEC	**13**	**50.12%**
SPARX	LGBM[1]	5	50.64%
	CNN[1]	5	50.38%
	LSTM[1]	5	50.45%
	LbEC	**6**	**50.62%**
	TbEC	**6**	**50.18%**
Piccolo-80	**LbEC**	**6**	**50.18%**
	TbEC	**9**	**50.05%**

[1] D. Pal, U. Mandal, M. Chaudhury, A. Das, and D. R. Chowdhury, "A deep neural differential distinguisher for ARX based block cipher." Cryptology ePrint Archive, Paper 2022/1195, 2022.

[2] E. Bellini, D. G erault, A. Hambitzer, and M. Rossi, "A cipher-agnostic neural training pipeline with automated finding of good input differences," IACR Trans. Symmetric Cryptol., vol. 2023, no. 3, pp. 184–212, 2023.

[3] L. Zhang and Z. Wang, "Improving differential-neural distinguisher model for des, chaskey, and present," 2022.

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Conclusion

- the problem of building differential distinguishers aided by deep learning is observed from a unique standpoint
- embedding vectors have represented the sequence tokens
- the embedding vectors representing the ciphertext sequences have been used for the classification tasks
- one hot encoding $\rightarrow LbEC$
- the model learns the embedding vectors during the training phase$\rightarrow TbEC$
- this is a generalized approach $\rightarrow$ the approach is clearly not specific to any particular design
- future scope $\rightarrow$ further improvements and extension of the method to other ciphers
- perform a key recovery with the help of the proposed distinguishers

THANK YOU