# A Note on the Bias of Rotational Differential-Linear Distinguishers 

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#### Abstract

This note solves the open problem of finding a closed formula for the bias of a rotational differential-linear distinguisher proposed in IACR ePrint 2021/189 (EUROCRYPT 2021), completely generalizing the results on ordinary differential-linear distinguishers due to Blondeau, Leander, and Nyberg (JoC 2017) to the case of rotational differentiallinear distinguishers.


Keywords: Rotational Differential-linear, • Differential-linear Attacks • Rotational Cryptanalysis • Multidimensional Differential-linear Attacks

## 1 Introduction

In LSL21, the framework of rotational differential-linear cryptanalysis was established by replacing the differential part of the differential-linear framework LH94|LGZL09|Lu15|BLN17|BDKW19 BLT20 with rotational-xor differentials KN10 KNR10 KNP ${ }^{+} 15$ KAR20 AJN14|MPS13|AL16|LWRA17 LLA ${ }^{+} 20$. This work left it as an open problem to derive a closed formula for the bias of a rotational differential-linear distinguisher. In this note, we solve this open problem and investigate the so-called multidimensional rotational differential-linear distinguishers, which completely generalizes the results on ordinary differentiallinear distinguishers due to Blondeau, Leander, and Nyberg [BLN17] to the case of rotational differential-linear distinguishers.

## 2 Notations and Preliminaries

Let $\mathbb{F}_{2}=\{0,1\}$ be the field with two elements. We denote by $x_{i}$ the $i$-th bit of a bit string $x \in \mathbb{F}_{2}^{n}$. For a vectorial Boolean function $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{m}$ with $y=F(x) \in \mathbb{F}_{2}^{m}$, its $i$-th output bit $y_{i}$ is denoted by $(F(x))_{i}$. The XOR-difference and rotational-xor difference with offset $t$ of two bit strings $x$ and $x^{\prime}$ in $\mathbb{F}_{2}^{n}$ are

[^0]defined as $x \oplus x^{\prime}$ and $(x \lll t) \oplus x^{\prime}$, respectively. For the rotational-xor difference $\delta=(x \lll t) \oplus x^{\prime}$, we may omit the rotation offset and write $\delta=\overleftarrow{x} \oplus x^{\prime}$ or $\delta=\operatorname{rot}(x) \oplus x^{\prime}$ to make the notation more compact when it is clear from the context. Correspondingly, $\vec{x}$ and $\operatorname{rot}^{-1}(x)$ rotate $x$ or its substrings to the right. Similar to differential cryptanalysis with XOR-difference, we can define the probability of an RX-differential as follows.

Definition 1 (RX-differential probability). Let $f: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be a vectorial boolean function. Let $\alpha$ and $\beta$ be n-bit words. Then, the $R X$-differential probability of the $R X$-differential $\alpha \rightarrow \beta$ for $f$ is defined as

$$
\operatorname{Pr}[\alpha \xrightarrow{\mathrm{RX}} \beta]=2^{-n} \#\left\{x \in \mathbb{F}_{2}^{n}: \operatorname{rot}(f(x)) \oplus f(\operatorname{rot}(x) \oplus \alpha)=\beta\right\}
$$

Finally, the definitions of correlation, bias, and some lemmas concerning Boolean functions together with the piling-up lemma are needed.

Definition 2 ([Car06Can16]). The correlation of a Boolean function $f$ : $\mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}$ is defined as $\operatorname{cor}(f)=2^{-n}\left(\#\left\{x \in \mathbb{F}_{2}^{n}: f(x)=0\right\}-\#\left\{x \in \mathbb{F}_{2}^{n}:\right.\right.$ $f(x)=1\})$.

Definition 3 ([Car06Can16]). The bias $\epsilon(f)$ of a Boolean function $f: \mathbb{F}_{2}^{n} \rightarrow$ $\mathbb{F}_{2}$ is defined as $2^{-n} \#\left\{x \in \mathbb{F}_{2}^{n}: f(x)=0\right\}-\frac{1}{2}$.
From Definition 2 and Definition 3 we can see that $\operatorname{cor}(f)=2 \epsilon(f)$.

Definition 4. Let $f: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}$ be a Boolean function. The Walsh-Hadamard transformation takes in $f$ and produces a real-valued function $\hat{f}: \mathbb{F}_{2}^{n} \rightarrow \mathbb{R}$ such that

$$
\forall w \in \mathbb{F}_{2}^{n}, \quad \hat{f}(w)=\sum_{x \in \mathbb{F}_{2}^{n}} f(x)(-1)^{x \cdot w}
$$

Definition 5. Let $f: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}$ and $g: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}$ be two Boolean functions. The convolutional product of $f$ and $g$ is a Boolean function defined as

$$
\forall y \in \mathbb{F}_{2}^{n}, \quad(f \star g)(y)=\sum_{x \in \mathbb{F}_{2}^{n}} g(x) f(x \oplus y)
$$

Lemma 1 (Car06], Corollary 2). Let $\hat{f}$ be the Walsh-Hadamard transformation of $f$. Then the Walsh-Hadamard transformation of $\hat{f}$ is $2^{n} f$.
Lemma 2 ([Car06], Proposition 6). $\widehat{(f \star g)}(z)=\hat{f}(z) \hat{g}(z)$ and thus $\widehat{(f \star f)}=$ $(\hat{f})^{2}$.
Lemma 3 (Piling-up Lemma Mat93]). Let $Z_{0}, \cdots, Z_{m-1}$ be $m$ independent binary random variables with $\operatorname{Pr}\left[Z_{i}=0\right]=p_{i}$. Then we have that

$$
\operatorname{Pr}\left[Z_{0} \oplus \cdots \oplus Z_{m-1}=0\right]=\frac{1}{2}+2^{m-1} \prod_{i=0}^{m-1}\left(p_{i}-\frac{1}{2}\right)
$$

or alternatively, $2 \operatorname{Pr}\left[Z_{0} \oplus \cdots \oplus Z_{m-1}=0\right]-1=\prod_{i=0}^{m-1}\left(2 p_{i}-1\right)$.

## 3 Rotational Differential-linear cryptanalysis

A natural extension of the differential-linear cryptanalysis is to replace the differential part of the attack by rotational-xor (RX) differentials. Let $E=E_{1} \circ E_{0}$ be an encryption function. Assume that we have an RX-differential $\delta \rightarrow \Delta$ covering $E_{0}$ with $\operatorname{Pr}\left[\operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}(\operatorname{rot}(x) \oplus \delta)=\Delta\right]=p$ and a linear approximation $\Gamma \rightarrow \gamma$ of $E_{1}$ such that

$$
\left\{\begin{array}{l}
\epsilon_{\Gamma, \gamma}=\operatorname{Pr}\left[\Gamma \cdot y \oplus \gamma \cdot E_{1}(y)=0\right]-\frac{1}{2} \\
\epsilon_{\mathrm{rot}^{-1}(\Gamma), \operatorname{rot}^{-1}(\gamma)}=\operatorname{Pr}\left[\operatorname{rot}^{-1}(\Gamma) \cdot y \oplus \operatorname{rot}^{-1}(\gamma) \cdot E_{1}(y)=0\right]-\frac{1}{2}
\end{array}\right.
$$

Let $x^{\prime}=\operatorname{rot}(x) \oplus \delta$. If the assumption

$$
\begin{equation*}
\operatorname{Pr}\left[\Gamma \cdot\left(\operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}\left(x^{\prime}\right)\right)=0 \mid \operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}\left(x^{\prime}\right) \neq \Delta\right]=\frac{1}{2} \tag{1}
\end{equation*}
$$

holds. We have

$$
\operatorname{Pr}\left[\Gamma \cdot\left(\operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}\left(x^{\prime}\right)\right)=0\right]=\frac{1}{2}+\frac{(-1)^{\Gamma \cdot \Delta}}{2} p
$$

Since

$$
\begin{aligned}
\gamma \cdot\left(\operatorname{rot}(E(x)) \oplus E\left(x^{\prime}\right)\right) & =\gamma \cdot \operatorname{rot}(E(x)) \oplus \Gamma \cdot \operatorname{rot}\left(E_{0}(x)\right) \\
& \oplus \Gamma \cdot\left(\operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}\left(x^{\prime}\right)\right) \\
& \oplus \Gamma \cdot E_{0}\left(x^{\prime}\right) \oplus \gamma \cdot E\left(x^{\prime}\right) \\
& =\operatorname{rot}\left(\operatorname{rot}^{-1}(\gamma) \cdot E(x) \oplus \operatorname{rot}^{-1}(\Gamma) \cdot E_{0}(x)\right) \\
& \oplus \Gamma \cdot\left(\operatorname{rot}\left(E_{0}(x)\right) \oplus E_{0}\left(x^{\prime}\right)\right) \\
& \oplus \Gamma \cdot E_{0}\left(x^{\prime}\right) \oplus \gamma \cdot E\left(x^{\prime}\right)
\end{aligned}
$$

the bias of the rotational differential-linear distinguisher can be estimated by piling-up lemma as

$$
\mathcal{E}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}=\operatorname{Pr}\left[\gamma \cdot\left(\overleftarrow{E}(x) \oplus E\left(x^{\prime}\right)\right)=0\right]-\frac{1}{2}=(-1)^{\Gamma \cdot \Delta} \cdot 2 p \epsilon_{\Gamma, \gamma} \epsilon_{\mathrm{rot}^{-1}(\Gamma), \mathrm{rot}^{-1}(\gamma)}
$$

and the corresponding correlation of the distinguisher is

$$
\mathcal{C}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}=2 \mathcal{E}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}=(-1)^{\Gamma \cdot \Delta} \cdot 4 p \epsilon_{\Gamma, \gamma} \epsilon_{\mathrm{rot}^{-1}(\Gamma), \text { rot }-1}(\gamma)
$$

We can distinguish $E$ from random permutations if the absolute value of $\mathcal{E}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}$ or $\mathcal{C}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}$ is sufficiently high. Note that if we set the rotation offset to zero, the rotational differential-linear attack is exactly the ordinary differential-linear cryptanalysis. Therefore, the rotational differential-linear attack is a strict generalization of the ordinary differential-linear cryptanalysis. However, as in ordinary differential-linear attacks, the assumption described by Equation (1) may not hold in practice, and we prefer a closed formula for the bias $\mathcal{E}_{\delta, \gamma}^{\mathrm{R}-\mathrm{DL}}$ without this assumption for much the same reasons leading to Blondeau, Leander, and Nyberg's work BLN17.

## 4 The Bias of A Rotational Differential-Linear Distinguisher

In [BLN17], Blondeau, Leander, and Nyberg proved the following theorem based on the general link between differential and linear cryptanalysis CV94.

Theorem 1 ([BLN17]). If $E_{0}$ and $E_{1}$ are independent, the bias of a differentiallinear distinguisher with input difference $\delta$ and output linear mask $\gamma$ can be computed as

$$
\begin{equation*}
\mathcal{E}_{\delta, \gamma}=\sum_{v \in \mathbb{F}_{2}^{n}} \epsilon_{\delta, v} c_{v, \gamma}^{2}, \tag{2}
\end{equation*}
$$

for all $\delta \neq 0$ and $\gamma \neq 0$, where

$$
\left\{\begin{array}{l}
\epsilon_{\delta, v}=\operatorname{Pr}\left[v \cdot\left(E_{0}(x) \oplus E_{0}(x \oplus \delta)\right)=0\right]-\frac{1}{2} \\
c_{v, \gamma}=\operatorname{cor}\left(v \cdot y \oplus \gamma \cdot E_{1}(y)\right)
\end{array} .\right.
$$

To replay Blondeau, Leander, and Nyberg's technique in an attempt to derive the rotational differential-linear counterpart of Equation (2), we have to first establish the relationship between rotational differential-linear cryptanalysis and linear cryptanalysis.

### 4.1 The Link between RX and Linear Cryptanalysis

Let $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be a vectorial Boolean function. The cardinality of the set

$$
\left\{x \in \mathbb{F}_{2}^{n}: \overleftarrow{F}(x) \oplus F(\overleftarrow{x} \oplus a)=b\right\}
$$

is denoted by $\xi_{F}(a, b)$, and the correlation of $u \cdot x \oplus v \cdot F(x)$ is $\operatorname{cor}(u \cdot x \oplus v \cdot F(x))$. Let $\underset{\rightarrow}{\overleftarrow{F}}: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be the vectorial Boolean function mapping $x$ to $\overleftarrow{F}(\vec{x})$. It is easy to show that $\operatorname{cor}(u \cdot x \oplus v \cdot \underset{\vec{F}}{( }(x))=\operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x))$. In what follows, we are going to establish the relationship between

$$
\xi_{F}(a, b), \quad \operatorname{cor}(u \cdot x \oplus v \cdot F(x)), \quad \text { and } \operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x))
$$

Definition 6. Given a vectorial Boolean function $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$, the Boolean function $\theta_{F}: \mathbb{F}_{2}^{2 n} \rightarrow \mathbb{F}_{2}$ is defined as

$$
\theta_{F}(x, y)= \begin{cases}1 & \text { if } y=F(x) \\ 0 & \text { otherwise }\end{cases}
$$

Lemma 4. Let $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be a vectorial Boolean function. Then for any $(a, b) \in \mathbb{F}_{2}^{2 n}$, we have $\xi_{F}(a, b)=\left(\theta_{\underset{\underline{F}}{ }} \star \theta_{F}\right)(a, b)$.

Proof. According to Definition 5, we have

$$
\begin{aligned}
& \left(\theta_{\underset{\rightarrow}{\leftrightarrows}} \star \theta_{F}\right)(a, b)=\sum_{x \| y \in \mathbb{F}_{2}^{2 n}} \theta_{\overleftarrow{\rightarrow}}(x, y) \theta_{F}(a \oplus x, b \oplus y) \\
& =\sum_{x \in \mathbb{F}_{2}^{n}} \sum_{y \in \mathbb{F}_{2}^{n}} \theta_{\overleftarrow{\rightarrow}}(x, y) \theta_{F}(a \oplus x, b \oplus y) \\
& =\sum_{x \in \mathbb{F}_{2}^{n}} \theta_{\overleftarrow{G}}(x, \underset{\rightarrow}{\overleftarrow{F}}(x)) \theta_{F}(a \oplus x, b \oplus \underset{\rightarrow}{\overleftarrow{F}}(x))=\sum_{x \in \mathbb{F}_{2}^{n}} \theta_{F}(a \oplus x, b \oplus \underset{\rightarrow}{\overleftarrow{F}}(x)) \\
& =\#\left\{x \in \mathbb{F}_{2}^{n}: b \oplus \underset{\rightarrow}{\underset{F}{F}}(x)=F(a \oplus x)\right\}=\xi_{F}(a, b) .
\end{aligned}
$$

Lemma 5. Let $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be a vectorial Boolean function. Then for any $(a, b) \in \mathbb{F}_{2}^{2 n}$, we have $\operatorname{cor}(a \cdot x \oplus b \cdot F(x))=2^{-n} \hat{\theta}_{F}(a, b)$.
Proof. According to Definition 4, we have

$$
\begin{aligned}
\hat{\theta}_{F}(a, b) & =\sum_{x \| y \in \mathbb{F}_{2}^{2 n}} \theta_{F}(x, y)(-1)^{(x \| y) \cdot(a \| b)} \\
& =\sum_{x \in \mathbb{F}_{2}^{n}} \sum_{y \in \mathbb{F}_{2}^{n}} \theta_{F}(x, y)(-1)^{a \cdot x \oplus b \cdot y} \\
& =\sum_{x \in \mathbb{F}_{2}^{n}}(-1)^{a \cdot x \oplus b \cdot F(x)}=2^{n} \operatorname{cor}(a \cdot x \oplus b \cdot F(x))
\end{aligned}
$$

In addition, applying Lemma 5 to $\underset{\rightarrow}{\overleftarrow{F}}$ gives $\operatorname{cor}(a \cdot x \oplus b \cdot \underset{\rightarrow}{\overleftarrow{F}}(x))=\frac{1}{2^{n}} \underset{\underset{\rightarrow}{ }}{\underset{\boldsymbol{F}}{ }}(a, b)$
Theorem 2. The link between $R X$-differentials and linear approximations can be summarized as

$$
\xi_{F}(a, b)=\sum_{u \in \mathbb{F}_{2}^{n}} \sum_{v \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x)) .
$$

Proof. According to Lemma 4 and Lemma 2, we have

$$
2^{2 n} \xi_{F}(a, b)=(\widehat{\widehat{\underset{G}{\leftrightarrows}} \star})(a, b)=\widehat{\hat{\theta}_{\overleftarrow{F}} \hat{\theta}_{F}}(a, b)
$$

Since $\underset{\rightarrow}{\hat{\theta}_{\overleftrightarrow{F}}} \hat{\theta}_{F}=2^{2 n} \operatorname{cor}(u \cdot x \oplus v \cdot \underset{\rightarrow}{\overleftarrow{F}}(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))$ due to Lemma 5

$$
\begin{aligned}
\widehat{\hat{\theta}_{\widehat{F}} \hat{\theta}_{F}}(a, b) & =2^{2 n} \sum_{u \| v \in \mathbb{F}_{2}^{2 n}}(-1)^{(u \| v) \cdot(a \| \mid b)} \operatorname{cor}(u \cdot x \oplus v \cdot \underset{\rightarrow}{\overleftarrow{F}}(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x)) \\
& =2^{2 n} \sum_{u, v \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{cor}(u \cdot x \oplus v \cdot \overleftrightarrow{\rightarrow}(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x)) \\
& =2^{2 n} \sum_{u, v \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))
\end{aligned}
$$

If the function $F$ is rotation invariant, i.e., $\overleftarrow{F(x)}=F(\overleftarrow{x})$, then we have $\operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x))=\operatorname{cor}(u \cdot x \oplus v \cdot F(x))$. As a result, the theoretical link between rotational-xor and linear cryptanalysis degenerates to the link between ordinary differential cryptanalysis and linear cryptanalysis. Moreover, based on the link between differential and linear cryptanalysis, Blondeau, Leander, and Nyberg derived a closed formula for the bias of an ordinary differential-linear distinguisher as shown in Equation (22). We now try to mimic Blondeau, Leander, and Nyberg's approach to obtain a closed formula for the bias of rotational differential-linear distinguishers.

Note that this attempt was failed in LSL21 and it was noted that this was due to a fundamental difference between rotational-xor differentials and ordinary differentials: the output RX-difference is not necessarily zero when the input RXdifference $\operatorname{rot}(x) \oplus x^{\prime}$ is zero. In this work, we show that the difficulty brought by the difference is only technical.

### 4.2 A Closed Formula

Hereafter, we will denote $\operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))$ by $\lambda_{F}(u, v)$.
Definition 7. Let $V \subseteq \mathbb{F}_{2}^{n}$ be a linear space and $\delta \in \mathbb{F}_{2}^{n}$ be a given vector. The probability of an $R X$-differential from $\delta$ to $V$ is defined as

$$
\operatorname{Pr}[\delta \underset{F}{\mathrm{RX}} V]=\sum_{b \in V} \operatorname{Pr}[\delta \xrightarrow[F]{\mathrm{RX}} b] .
$$

Definition 8. Let $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$ be a vectorial Boolean function. The probability of the $R X$-differential from a linear space $U \subseteq \mathbb{F}_{2}^{n}$ to a linear space $V \subseteq \mathbb{F}_{2}^{n}$ for $F$ is defined as

$$
\begin{aligned}
\operatorname{Pr}[U \xrightarrow[F]{\mathrm{RX}} V] & =\frac{1}{2^{n} \cdot|U|} \#\left\{(x, a) \in \mathbb{F}_{2}^{n} \times U: \overleftarrow{F}(x) \oplus F(\overleftarrow{x} \oplus a) \in V\right\} \\
& =\frac{1}{2^{n} \cdot|U|} \#\left\{(x, a, b) \in \mathbb{F}_{2}^{n} \times U \times V: \overleftarrow{F}(x) \oplus F(\overleftarrow{x} \oplus a)=b\right\} \\
& =\frac{1}{|U|} \sum_{a \in U} \sum_{b \in V} \operatorname{Pr}[a \xrightarrow[F]{\mathrm{RX}} b]=\frac{1}{|U|} \sum_{a \in U} \operatorname{Pr}[a \xrightarrow[F]{\mathrm{RX}} V]
\end{aligned}
$$

Denote by $\operatorname{sp}(\delta)$ the linear space spanned by $\delta$. According to Definition 8 and Definition 7, we have

$$
\operatorname{Pr}[\operatorname{sp}(\delta) \xrightarrow[F]{\mathrm{RX}} V]=\frac{1}{2} \operatorname{Pr}[\delta \xrightarrow[F]{\mathrm{RX}} V]+\frac{1}{2} \operatorname{Pr}[0 \xrightarrow[F]{\mathrm{RX}} V],
$$

which implies that

$$
\begin{equation*}
\operatorname{Pr}[\delta \xrightarrow[F]{\mathrm{RX}} V]=2 \operatorname{Pr}[\operatorname{sp}(\delta) \xrightarrow[F]{\mathrm{RX}} V]-\operatorname{Pr}[0 \xrightarrow[F]{\mathrm{RX}} V] . \tag{3}
\end{equation*}
$$

Lemma 6 ([Bon20]). Let $\mathcal{H}$ be an additive subgroup of $\mathbb{F}_{2}^{n}$ and $f: \mathbb{F}_{2}^{n} \rightarrow \mathbb{R}$ be a function. Then

$$
f(x)=\sum_{h \in \mathcal{H}}(-1)^{x \cdot h}= \begin{cases}|\mathcal{H}|, & x \in \mathcal{H}^{\perp} \\ 0, & x \notin \mathcal{H}^{\perp}\end{cases}
$$

Proof. Let $\left\{h_{1}, \cdots, h_{c}\right\}$ be a basis of $\mathcal{H}$, and thus $\mathcal{H}=\left\{\tau_{1} h_{1}+\cdots+\tau_{c} h_{c}\right.$ : $\left.\left(\tau_{1}, \cdots, \tau_{c}\right) \in \mathbb{F}_{2}^{c}\right\}$ has totally $2^{c}$ elements. Consequently, we have

$$
\begin{aligned}
\sum_{h \in \mathcal{H}}(-1)^{x \cdot h} & =\sum_{\left(\tau_{1}, \cdots, \tau_{c}\right) \in \mathbb{F}_{2}^{c}}(-1)^{x \cdot\left(\tau_{1} h_{1}+\cdots+\tau_{c} h_{c}\right)} \\
& =\sum_{\left(\tau_{1}, \cdots, \tau_{c}\right) \in \mathbb{F}_{2}^{c}}(-1)^{x \cdot \tau_{1} h_{1}} \cdots(-1)^{x \cdot \tau_{c} h_{c}} \\
& =\sum_{\tau_{1} \in \mathbb{F}_{2}}(-1)^{x \cdot \tau_{1} h_{1}} \cdots \sum_{\tau_{c} \in \mathbb{F}_{2}}(-1)^{x \cdot \tau_{c} h_{c}} \\
& =\left(1+(-1)^{x \cdot h_{1}}\right) \cdots\left(1+(-1)^{x \cdot h_{c}}\right),
\end{aligned}
$$

which equals to $\mathcal{H}=2^{c}$ if and only if $x \cdot h_{1}=\cdots=x \cdot h_{c}=0$.
Theorem 3. Let $U$ and $V$ be linear spaces in $\mathbb{F}_{2}^{n}$, then we have

$$
\operatorname{Pr}\left[U^{\perp} \xrightarrow[F]{\mathrm{RX}} V^{\perp}\right]=\frac{1}{|V|} \sum_{\substack{u \in U \\ v \in V}} \operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))
$$

Proof. Let $\lambda(u, v)=\operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))$. According to Definition 8 and Theorem 2 we have

$$
\begin{aligned}
\operatorname{Pr}\left[U^{\perp} \xrightarrow[F]{\mathrm{RX}} V^{\perp}\right] & =\frac{1}{\left|U^{\perp}\right|} \sum_{\substack{a \in U^{\perp}}} \frac{1}{2^{n}} \sum_{\substack{u \in \mathbb{F}_{2}^{n} \\
v \in \mathbb{F}_{2}^{n}}}(-1)^{u \cdot a \oplus v \cdot b} \lambda(u, v) \\
& =\frac{1}{2^{n}} \cdot \frac{1}{\left|U^{\perp}\right|} \sum_{\substack{u \in \mathbb{F}_{n}^{n} \\
v \in \mathbb{F}_{2}^{n}}} \lambda(u, v) \sum_{a \in U^{\perp}}(-1)^{u \cdot a} \sum_{b \in V^{\perp}}(-1)^{v \cdot b}
\end{aligned}
$$

Applying Lemma 6 gives

$$
\begin{aligned}
\operatorname{Pr}\left[U^{\perp} \xrightarrow[F]{\mathrm{RX}} V^{\perp}\right] & =\frac{1}{2^{n}} \cdot \frac{1}{\left|U^{\perp}\right|} \cdot\left|U^{\perp}\right| \cdot\left|V^{\perp}\right| \sum_{\substack{u \in U \\
v \in V}} \lambda(u, v) \\
& =\frac{1}{|V|} \sum_{\substack{u \in U \\
v \in V}} \lambda(u, v)
\end{aligned}
$$

Lemma 7. Let $\lambda(u, v)=\operatorname{cor}(\vec{u} \cdot x \oplus \vec{v} \cdot F(x)) \operatorname{cor}(u \cdot x \oplus v \cdot F(x))$. For $\Delta$, $w \in \mathbb{F}_{2}^{n}$, we have

$$
\begin{equation*}
\operatorname{Pr}\left[\Delta \xrightarrow[F]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]=\frac{1}{2} \sum_{u \in \operatorname{sp}(\Delta)^{\perp}} \lambda(u, w)-\frac{1}{2} \sum_{u \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(\Delta)^{\perp}} \lambda(u, w)+\frac{1}{2} \tag{4}
\end{equation*}
$$

Proof. According to Equation (3), we have

$$
\begin{aligned}
\operatorname{Pr}\left[\Delta \xrightarrow[F]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right] & =2 \operatorname{Pr}\left[\operatorname{sp}(\Delta) \xrightarrow[F]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]-\operatorname{Pr}\left[0 \xrightarrow[F]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right] \\
& =2 \cdot \frac{1}{2} \sum_{\substack{u \in \operatorname{sp}(\Delta)^{\perp} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)-\frac{1}{2} \sum_{\substack{u \in \mathbb{F}_{n}^{n} \\
v \in \operatorname{sp}(w)}} \lambda(u, v) \quad \quad \text { (Theorem 3) } \\
& =\frac{1}{2} \sum_{\substack{u \in \operatorname{sp}(\Delta)^{\perp} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)-\frac{1}{2}\left(\sum_{\substack{u \in \mathbb{F}_{2}^{n} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)-\sum_{\substack{u \in \operatorname{sp}(\Delta)^{\perp} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)\right) \\
& =\frac{1}{2} \sum_{\substack{u \in \operatorname{sp}(\Delta)^{\perp} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)-\frac{1}{2} \sum_{\substack{u \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(\Delta)^{\perp} \\
v \in \operatorname{sp}(w)}} \lambda(u, v)
\end{aligned}
$$

Since $\lambda(u, 0)=0$ for $u \neq 0$ and $\lambda(u, 0)=1$ for $u=0$,

$$
\operatorname{Pr}\left[\Delta \xrightarrow[F]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]=\frac{1}{2} \sum_{u \in \operatorname{sp}(\Delta)^{\perp}} \lambda(u, w)-\frac{1}{2} \sum_{u \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(\Delta)^{\perp}} \lambda(u, w)+\frac{1}{2}
$$

Theorem 4. If two parts $E_{0}$ and $E_{1}$ of an n-bit block cipher $E=E_{1} \circ E_{0}$ are $R X$-differentially independent, that is, for all $(a, b) \in \mathbb{F}_{2}^{n} \times \mathbb{F}_{2}^{n}$,

$$
\operatorname{Pr}[a \underset{E}{\mathrm{RX}} b]=\sum_{\Delta \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[a \underset{E_{0}}{\mathrm{RX}} \Delta\right] \cdot \operatorname{Pr}\left[\Delta \underset{E_{1}}{\mathrm{RX}} b\right]
$$

then we have

$$
\operatorname{Pr}\left[\delta \xrightarrow[E]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]-\frac{1}{2}=\sum_{u \in \mathbb{F}_{2}^{n}}\left(\operatorname{Pr}\left[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(u)^{\perp}\right]-\frac{1}{2}\right) \cdot \lambda_{E_{1}}(u, w)
$$

Proof. Substituting Equation (4) into the right-hand side of

$$
\operatorname{Pr}\left[\delta \xrightarrow[E]{\mathrm{RX}} \mathrm{sp}(w)^{\perp}\right]-\frac{1}{2}=\sum_{\Delta \in \mathbb{F}_{2}^{n}} \operatorname{Pr}[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \Delta] \operatorname{Pr}\left[\Delta \xrightarrow[E_{1}]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]-\frac{1}{2}
$$

gives

$$
\begin{equation*}
\frac{1}{2}\left(\sum_{\substack{\Delta \in \mathbb{F}_{2}^{n} \\ u \in \operatorname{sp}(\Delta)^{\perp}}} \operatorname{Pr}\left[\delta \underset{E_{0}}{\mathrm{RX}} \Delta\right] \lambda(u, w)-\sum_{\substack{\Delta \in \mathbb{F}_{2}^{n} \\ u \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(\Delta)^{\perp}}} \operatorname{Pr}[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \Delta] \lambda(u, w)\right) \tag{5}
\end{equation*}
$$

Since $\mathbb{S}=\left\{(u, \Delta): \Delta \in \mathbb{F}_{2}^{n}, u \in \operatorname{sp}(\Delta)^{\perp}\right\}=\left\{(u, \Delta): u \in \mathbb{F}_{2}^{n}, \Delta \in \operatorname{sp}(u)^{\perp}\right\}$ and thus $\left(\mathbb{F}_{2}^{n}, \mathbb{F}_{2}^{n}\right) \backslash \mathbb{S}=\left\{(u, \Delta): \Delta \in \mathbb{F}_{2}^{n}, u \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(\Delta)^{\perp}\right\}=\left\{(u, \Delta): u \in \mathbb{F}_{2}^{n}, \Delta \in\right.$ $\left.\mathbb{F}_{2}^{n} \backslash \operatorname{sp}(u)^{\perp}\right\}$, Equation (5) can be written as

$$
\begin{aligned}
& \frac{1}{2}\left(\sum_{\substack{u \in \mathbb{F}_{2}^{n} \\
\Delta \in \operatorname{sp}(u)^{\perp}}} \operatorname{Pr}[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \Delta] \lambda(u, w)-\sum_{\substack{u \in \mathbb{F}_{2}^{n} \\
\Delta \in \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(u)^{\perp}}} \operatorname{Pr}[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \Delta] \lambda(u, w)\right) \\
= & \frac{1}{2}\left(\sum_{u \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(u)^{\perp}\right] \lambda(u, w)-\sum_{u \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \mathbb{F}_{2}^{n} \backslash \operatorname{sp}(u)^{\perp}\right] \lambda(u, w)\right) \\
= & \sum_{u \in \mathbb{F}_{2}^{n}}\left(\operatorname{Pr}\left[\delta \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(u)^{\perp}\right]-\frac{1}{2}\right) \lambda(u, w) .
\end{aligned}
$$

### 4.3 The Multidimensional Case

Let $U$ and $W$ be subspaces of $\mathbb{F}_{2}^{n}$, we define the bias of the rotational differentiallinear distinguisher in the multidimensional case by

$$
\mathcal{E}_{U, W}^{\mathrm{R}-\mathrm{DL}}=\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E]{\mathrm{RX}} W^{\perp}\right]-\frac{1}{|W|}
$$

The following lemma can be regarded as the dual of Theorem 2 .
Lemma 8. For any permutation $F: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{n}$, we have

$$
\lambda_{F}(u, v)=\frac{1}{2^{n}} \sum_{a, b \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{Pr}[a \underset{F}{\mathrm{RX}} b] .
$$

Proof. According to Lemma 4 and Lemma 2, we have

$$
\hat{\xi}_{F}(u, v)=\left(\widehat{\theta_{\underset{G}{\leftrightarrows}} \widehat{\theta}_{F}}\right)(u, v)=\hat{\theta}_{\overleftarrow{G}} \hat{\theta}_{F}(u, v) .
$$

Applying Definition 4 and Lemma 5 gives

$$
2^{n} \sum_{a, b \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{Pr}[a \underset{F}{\mathrm{RX}} b]=2^{2 n} \lambda_{F}(u, v),
$$

which completes the proof.
Lemma 9. If two parts $E_{0}$ and $E_{1}$ of an n-bit block cipher $E=E_{1} \circ E_{0}$ are $R X$-differentially independent, that is, for all $(a, b) \in \mathbb{F}_{2}^{n} \times \mathbb{F}_{2}^{n}$,

$$
\operatorname{Pr}[a \underset{E}{\mathrm{RX}} b]=\sum_{\Delta \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[a \underset{E_{0}}{\mathrm{RX}} \Delta\right] \cdot \operatorname{Pr}[\Delta \xrightarrow[E_{1}]{\mathrm{RX}} b],
$$

then for all $u, w \in \mathbb{F}_{2}^{n}$, we have $\lambda_{E}(u, w)=\sum_{v \in \mathbb{F}_{2}^{n}} \lambda_{E_{0}}(u, v) \lambda_{E_{1}}(v, w)$.

Proof. According to Lemma 8, we have

$$
\lambda_{E}(u, w)=\frac{1}{2^{n}} \sum_{a, b \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \operatorname{Pr}[a \underset{F}{\mathrm{RX}} b]
$$

Since $E_{0}$ and $E_{1}$ are RX-differentially independent,

$$
\lambda_{E}(u, w)=\frac{1}{2^{n}} \sum_{a, b \in \mathbb{F}_{2}^{n}}(-1)^{u \cdot a \oplus v \cdot b} \sum_{c \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[a \underset{E_{0}}{\mathrm{RX}} c\right] \cdot \operatorname{Pr}\left[c \underset{E_{1}}{\mathrm{RX}} b\right] .
$$

Applying Theorem 2 gives

$$
\begin{aligned}
\lambda_{E}(u, w) & =\frac{1}{2^{2 n}} \sum_{c \in \mathbb{F}_{2}^{n}} \sum_{m, v \in \mathbb{F}_{2}^{n}} \sum_{a \in \mathbb{F}_{2}^{n}}(-1)^{(u \oplus m) \cdot a \oplus c \cdot v} \lambda_{E_{0}}(m, v) \sum_{b \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[c \underset{E_{1}}{\mathrm{RX}} b\right] \\
& =\frac{1}{2^{3 n}} \sum_{m, v \in \mathbb{F}_{2}^{n}} \sum_{s, p \in \mathbb{F}_{2}^{n}} \lambda_{E_{0}}(m, v) \lambda_{E_{1}}(p, s) \sum_{a \in \mathbb{F}_{2}^{n}}(-1)^{(u \oplus m) \cdot a} \sum_{b \in \mathbb{F}_{2}^{n}}(-1)^{(w \oplus s) \cdot b} \sum_{c \in \mathbb{F}_{2}^{n}}(-1)^{(v \oplus p) \cdot c} \\
& =\sum_{v \in \mathbb{F}_{2}^{n}} \lambda_{E_{0}}(u, v) \lambda_{E_{1}}(v, w)
\end{aligned}
$$

Theorem 5. If two parts $E_{0}$ and $E_{1}$ of an n-bit block cipher $E=E_{1} \circ E_{0}$ are $R X$-differentially independent, that is, for all $(a, b) \in \mathbb{F}_{2}^{n} \times \mathbb{F}_{2}^{n}$,

$$
\operatorname{Pr}[a \underset{E}{\mathrm{RX}} b]=\sum_{\Delta \in \mathbb{F}_{2}^{n}} \operatorname{Pr}\left[a \underset{E_{0}}{\mathrm{RX}} \Delta\right] \cdot \operatorname{Pr}\left[\Delta \underset{E_{1}}{\mathrm{RX}} b\right]
$$

then we have

$$
\mathcal{E}_{U, W}^{\mathrm{R}-\mathrm{DL}}=\frac{2}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}} \epsilon_{U, v}^{\mathrm{R}-\mathrm{DL}} C_{v, W}^{\mathrm{R}-\mathrm{DL}}
$$

where $\epsilon_{U, v}^{\mathrm{R}-\mathrm{DL}}=\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]$ and $C_{v, W}^{\mathrm{R}-\mathrm{DL}}=\sum_{w \in W \backslash\{0\}} \lambda_{E_{1}}(v, w)$.
Proof. According to the Theorem 2, we have

$$
\begin{aligned}
\operatorname{Pr}\left[U^{\perp} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right] & =\frac{1}{2} \sum_{\substack{u \in U \\
v \in \operatorname{sp}(w)}} \lambda_{E_{0}}(u, v) \\
& =\frac{1}{2} \sum_{u \in U} \lambda_{E_{0}}(u, v)+\frac{1}{2} \sum_{u \in U} \lambda_{E_{0}}(u, 0) \\
& =\frac{1}{2} \sum_{u \in U} \lambda_{E_{0}}(u, v)+\frac{1}{2}
\end{aligned}
$$

Thus,

$$
\begin{equation*}
2 \operatorname{Pr}\left[U^{\perp} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(w)^{\perp}\right]-1=\sum_{u \in U} \lambda_{E_{0}}(u, v) \tag{6}
\end{equation*}
$$

For any subspaces $U$ and $W \subseteq \mathbb{F}_{2}^{n}$, we have

$$
\begin{aligned}
& \operatorname{Pr}\left[U^{\perp} \xrightarrow[E]{\mathrm{RX}} W^{\perp}\right] \\
= & \frac{1}{|W|} \sum_{\substack{u \in U \\
w \in W}} \lambda_{E}(u, w) \\
= & \frac{1}{|W|} \sum_{\substack{u \in U \\
w \in W \\
v \in \mathbb{F}_{2}^{n}}} \lambda_{E_{0}}(u, v) \lambda_{E_{1}}(v, w) \quad \text { (Lemma 9) } \\
= & \frac{1}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}} \sum_{u \in U} \lambda_{E_{0}}(u, v) \sum_{w \in W} \lambda_{E_{1}}(v, w) \quad \text { (Equation (6)) } \\
= & \sum_{v \in \mathbb{F}_{2}^{n}} \frac{1}{|W|}\left(2 \operatorname{Pr}\left[U^{\perp} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w) .
\end{aligned}
$$

Thus, when $U=\{0\}=\left(\mathbb{F}_{2}^{n}\right)^{\perp}$,

$$
\operatorname{Pr}\left[U^{\perp} \xrightarrow[E]{\mathrm{RX}} W^{\perp}\right]=\sum_{v \in \mathbb{F}_{2}^{n}} \frac{1}{|W|}\left(2 \operatorname{Pr}\left[0 \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w) .
$$

According to Definition 8, for any $F$, the following relation holds

$$
\left(\left|U^{\perp}\right|-1\right) \operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[F]{\mathrm{RX}} W^{\perp}\right]=\left|U^{\perp}\right| \operatorname{Pr}\left[U^{\perp} \xrightarrow[F]{\mathrm{RX}} W^{\perp}\right]-\operatorname{Pr}\left[0 \xrightarrow[F]{\mathrm{RX}} W^{\perp}\right]
$$

Then, we have

$$
\begin{aligned}
& \left(\left|U^{\perp}\right|-1\right) \operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[F]{\mathrm{RX}} W^{\perp}\right] \\
= & \sum_{v \in \mathbb{F}_{2}^{n}} \frac{1}{|W|}\left|U^{\perp}\right|\left(2 \operatorname{Pr}\left[U^{\perp} \xrightarrow[E_{0}]{\mathrm{RX}} \mathrm{sp}(v)^{\perp}\right]-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w) \\
- & \sum_{v \in \mathbb{F}_{2}^{n}} \frac{1}{|W|}\left(2 \operatorname{Pr}\left[0 \underset{E_{0}}{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w) \\
= & \frac{1}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}} 2\left(\left|U^{\perp}\right| \operatorname{Pr}\left[U^{\perp} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-\operatorname{Pr}\left[0 \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]\right)-\left(\left|U^{\perp}\right|-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w) \\
= & \frac{1}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}} 2\left(\left|U^{\perp}\right|-1\right) \operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-\left(\left|U^{\perp}\right|-1\right) \sum_{w \in W} \lambda_{E_{1}}(v, w)
\end{aligned}
$$

Dividing both sides by $\left|U^{\perp}\right|-1$ gives

$$
\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \underset{F}{\mathrm{RX}} W^{\perp}\right]=\frac{2}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}}\left(\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{Sp}(v)^{\perp}\right]-\frac{1}{2}\right) \sum_{w \in W} \lambda_{E_{1}}(v, w)
$$

Since $\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(0)^{\perp}\right]=1, \lambda(u, 0)=0$ for $u \neq 0$ and $\lambda(u, 0)=1$ for $u=0, \operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[F]{\mathrm{RX}} W^{\perp}\right]$ can be computed as

$$
\frac{2}{|W|} \sum_{v \in \mathbb{F}_{2}^{n}}\left(\operatorname{Pr}\left[U^{\perp} \backslash\{0\} \xrightarrow[E_{0}]{\mathrm{RX}} \operatorname{sp}(v)^{\perp}\right]-\frac{1}{2}\right) \sum_{\substack{w \in W \\ w \neq 0}} \lambda_{E_{1}}(v, w)+\frac{1}{|W|}
$$

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