#### **APPENDIX**

## A MATHEMATICAL PROOFS

### A.1 Preliminaries

We derive a lemma to bound the sum of n random variables. This lemma is similar to the Hoeffding bound but cannot be replaced by Hoeffding.

LEMMA 1. Let  $X_1, \ldots, X_n$  be n random variables such that  $X_i \in \{0, s_i\},$   $\Pr(X_i = s_i \mid X_1, \cdots, X_{i-1}) \leqslant p,$  where  $0 \leqslant s_i \leqslant 1$ . Let  $X = \sum_{i=1}^n X_i$ , and  $\mu = \sum_{i=1}^n ps_i = nmp$ .  $\Pr(X > (1 + \Lambda)\mu) \leqslant e^{-(\Delta - (e-2))nmp}$ 

PROOF. For any t > 0, by using the Markov inequality we have

$$\Pr(X > (1+\Delta)\mu) = \Pr(e^X > e^{(1+\Delta)\mu}) \leqslant \frac{E(e^X)}{e^{(1+\Delta)\mu}}$$

According to the conditions, we have

$$E(e^{X}) = E\left(E(e^{\sum_{i=1}^{n} X_{i}} \mid X_{1}, \dots, X_{n-1})\right)$$

$$= E\left(e^{\sum_{i=1}^{n-1} X_{i}} \cdot \Pr(X_{n} = 0 \mid X_{1}, \dots, X_{n-1})\right)$$

$$+e^{s_{n} + \sum_{i=1}^{n-1} X_{i}} \cdot \Pr(X_{n} = s_{n} \mid X_{1}, \dots, X_{n-1})\right)$$

$$\leq E\left(e^{\sum_{i=1}^{n-1} X_{i}}\right) \cdot \left(1 + p\left(e^{s_{n}} - 1\right)\right) \leq \dots \leq \prod_{i=1}^{n} \left(1 + p\left(e^{s_{i}} - 1\right)\right)$$

Because of  $1 + x < e^x$ , we have

$$E(e^X) \leqslant \prod_{i=1}^n e^{p(e^{s_i}-1)}.$$

Since for  $s_i \le 1$ , there is  $e^{s_i} - 1 \le (e - 1)s_i$ , so there is

$$E(e^X) \leq e^{\sum_{i=1}^n p(e-1)s_i} = e^{(e-1)mnp}.$$

That is

$$Pr(X > (1+\Delta)\mu) \leqslant \frac{e^{(e-1)nmp}}{e^{(1+\Delta)nmp}} = e^{-(\Delta - (e-2))nmp}$$

# A.2 Definition of Symbols

- (1)  $S_i$ :  $\{e_1, \dots, e_{N_i}\}$ , the set of keys entering the *i*-th layer, where  $N_i = |S_i|$ .
- (2)  $f_i(e)$ : the number of times that key e enters the i-th layer.
- (3)  $S_i^0$ : { $e \mid e \in S_i \land \forall i' \leq i, f_{i'}(e) \leq \frac{\lambda_{i'}}{2}$ }, the set of mice keys.
- (4)  $S_i^1$ :  $\{e \mid e \in S_i \land \exists i' \leq i, f_{i'}(e) > \frac{\lambda_{i'}}{2}\}$ , the set of elephant keys.
- (5)  $F_i$ :  $\sum_{\{e \in S_i^0\}} f_i(e)$ , the total frequency of mice keys in  $S_i^0$ .
- (6)  $C_i$ :  $|S_i^1|$ , the number of elephant keys in  $S_i^1$ .
- (7)  $S_{i,j}^0$ : { $e \mid e \in S_i^0 \land h(e) = j$ }, the set of mice keys that are mapped to the j-th bucket.
- (8)  $S_{i,j}^1$ : { $e \mid e \in S_i^1 \land h(e) = j$ }, the set of elephant keys that are mapped to the j-th bucket.
- (9)  $F_{i,j}$ :  $\sum_{\{e \in S_{i,j}^0\}} f_i(e)$ , the total frequency of mice keys in  $S_{i,j}^0$ .

- (10)  $C_{i,j}$ :  $|S_{i,j}^1|$ , the number of elephant keys in  $S_{i,j}^1$ .
- (11)  $\mathcal{P}_{i,k}$ :  $\{e_1, \dots, e_k\}$ , a subset of  $\mathcal{S}_i$  composed of the first k keys.
- (12)  $f_{i,k}^P : \sum_{\{e \in \mathcal{P}_{i,k-1} \cap \mathcal{S}_{i,h(e_k)}^0\}} f_i(e)$ , the total frequency of mice keys with a smaller index that conflicts with key  $e_k$ .
- (13)  $c_{i,k}^P$ :  $\left|\left\{e \mid e \in \mathcal{P}_{i,k-1} \cap \mathcal{S}_{i,h(e_k)}^1\right\}\right|$ , the number of elephant keys with a smaller index that conflicts with key  $e_k$ .

## A.3 Properties in One Layer

This section aims to prove that only a small proportion of the keys inserted into the i-th layer will be inserted into the (i+1)-th layer.

THEOREM A.1. (Theorem 1) Let

$$X_{i,k} = \begin{cases} 0 & C_{i,h(e_k)} = 0 \land f_{i,k}^P \leqslant \frac{\lambda_i}{2} \\ f_i(e_k) & C_{i,h(e_k)} = 0 \land f_{i,k}^P > \frac{\lambda_i}{2} \end{cases}, \quad X_i = \sum_{\{e_k \in \mathcal{S}_i^0\}} X_{i,k}.$$

The total frequency of the mice keys in the i-th layer leaving it does not exceed  $X_i$ , i.e.,

$$F_{i+1} \leqslant \sum_{\{e \in \mathcal{S}_i^0 \cap \mathcal{S}_{i+1}\}} f_{i+1}(e) \leqslant X_i.$$

PROOF. For the mice keys in the j-th bucket of the i-th layer, let the number of times they leave be  $F'_{i,j} = \sum_{\{e \in S^0_{i,j} \cap S^0_{i+1}\}} f_{i+1}(e)$ . Since a bucket can hold at least  $\lambda_i$  packets of the key, we have:

$$\begin{cases} F'_{i,j} = 0 & C_{i,j} = 0 \land F_{i,j} \leq \lambda_i \\ F'_{i,j} \leq F_{i,j} - \lambda_i & Cs_{i,j} = 0 \land F_{i,j} > \lambda_i \\ F'_{i,j} \leq F_{i,j} & C_{i,j} > 0 \end{cases}.$$

When  $C_{i,j} = 0 \land F_{i,j} > \lambda_i$ , exists k' satisfies

$$\sum_{\{e_k \in \mathcal{S}_{i,i}^0 \land k < k'\}} f_i(e_k) \leqslant \frac{\lambda_i}{2} \leqslant \sum_{\{e_k \in \mathcal{S}_{i,i}^0 \land k \leqslant k'\}} f_i(e_k) \leqslant \lambda_i.$$

Then for and only for any  $e_k \in S_{i,j}^0 \land k \leqslant k'$ , there is  $X_{i,k} = 0$ , and

$$\begin{split} F'_{i,j} &\leqslant \left(\sum_{\{e_k \in S^0_{i,j} \land k \leqslant k'\}} f_i(e_k) + \sum_{\{e_k \in S^0_{i,j} \land k > k'\}} f_i(e_k)\right) - \lambda_i \\ &\leqslant 0 + \sum_{\{e_k \in S^0_{i,j} \land k > k'\}} f_i(e_k) \\ &\leqslant \sum_{\{e_k \in S^0_{i,j} \land k \leqslant k'\}} X_{i,k} + \sum_{\{e_k \in S^0_{i,j} \land k > k'\}} X_{i,k}. \end{split}$$

Then we have  $F'_{i,j} \leqslant \sum_{\{e_k \in S^0_{i,j}\}} X_{i,k}$ , and

$$\sum_{\{e \in S_i^0 \cap S_{i+1}\}} f_{i+1}(e) = \sum_{j=1}^{w_i} F'_{i,j} \leqslant \sum_{j=1}^{w_i} \sum_{\{e_k \in S_{i,j}^0\}} X_{i,k} = X_i.$$

Similarly, we have the following lemma.

THEOREM A.2. Let

$$Y_{i,k} = \begin{cases} 0 & c_{i,k}^P = 0 \land F_{i,h(e_k)} \leq \lambda_i, \\ 2 & c_{i,k}^P = 0 \land F_{i,h(e_k)} > \lambda_i \\ 2 & c_{i,k}^P > 0. \end{cases} \quad Y_i = \sum_{e_k \in S_i^1} Y_{i,k}.$$

The number of distinct elephant keys in the i-th layer leaving it does not exceed  $Y_i$ , i.e.,

$$\left|S_i^1 \cap S_{i+1}^1\right| \leqslant Y_i$$
.

PROOF. For the elephant keys in the j-th bucket of the i-th layer,  $\sum_{\{e_k \in \mathcal{S}_{i,j}^1\}} Y_{i,k} < C_{i,j}$  if and only if  $C_{i,j} = 1 \land F_{i,j} \leqslant \lambda_i$ . In this case, the number of collisions in the bucket does not exceed  $\lambda_i$ , and no key enters the (i+1)-th layer. Thus we have  $|\mathcal{S}_{i,j}^1 \cap \mathcal{S}_{i+1}^1| \leqslant \sum_{\{e_k \in \mathcal{S}_{i,j}^1\}} Y_{i,j}$ , and

$$\left|S_{i}^{1} \cap S_{i+1}^{1}\right| = \sum_{j=1}^{w_{i}} \left|S_{i,j}^{1} \cap S_{i+1}^{1}\right| \leqslant \sum_{j=1}^{w_{i}} \sum_{\{e_{k} \in S_{i,j}^{1}\}} Y_{i,j} = Y_{i}.$$

Theorem A.3. Let  $W=\frac{4N(R_wR_\lambda)^6}{\Lambda(R_w-1)(R_\lambda-1)}$ ,  $\alpha_i=\frac{\|F\|_1}{(R_wR_\lambda)^{i-1}}$ ,  $\beta_i=\frac{\alpha_i}{\frac{\lambda_i}{2}}$ ,  $\gamma_i=(R_wR_\lambda)^{(2^{i-1}-1)}$ , and  $p_i=(R_wR_\lambda)^{-(2^{i-1}+4)}$ . Under the conditions of  $F_i\leqslant \frac{\alpha_i}{\gamma_i}$  and  $C_i\leqslant \frac{\beta_i}{\gamma_i}$ , we have:

$$\begin{split} & \Pr\left(X_{i,k} > 0 \mid X_{i,1}, \cdots, X_{i,k-1}\right) \leqslant p_i, \qquad \forall e_k \in \mathcal{S}_i^0. \\ & \Pr\left(Y_{i,k} > 0 \mid Y_{i,1}, \cdots, Y_{i,k-1}\right) \leqslant \frac{3}{4} p_i, \qquad \forall e_k \in \mathcal{S}_i^1. \end{split}$$

PROOF. By using Markov's inequality, we have

$$\Pr\left(X_{i,k} > 0 \mid X_{i,1}, \cdots, X_{i,k-1}\right) \\ = \Pr\left(\begin{pmatrix} C_{i,h(e_k)} = 0 \land f_{i,k}^P > \frac{\lambda_i}{2} \\ \lor & C_{i,h(e_k)} > 0 \end{pmatrix} \mid X_{i,1}, \cdots, X_{i,k-1} \end{pmatrix} \\ \leqslant \Pr\left(C_{i,h(e_k)} > 0 \mid X_{i,1}, \cdots, X_{i,k-1}\right) \\ \leqslant + \Pr\left(F_{i,h(e_k)} - f_i(e_k) > \frac{\lambda_i}{2} \mid X_{i,1}, \cdots, X_{i,k-1}\right) \\ \leqslant \frac{E(C_{i,h(e_k)} \mid X_{i,1}, \cdots, X_{i,k-1})}{1} \\ \leqslant \frac{E(F_{i,h(e_k)} - f_i(e_k) \mid X_{i,1}, \cdots, X_{i,k-1})}{\frac{\lambda_i}{2}} \\ \leqslant \frac{C_i}{w_i} + \frac{2F_i}{\lambda_i w_i}$$

$$\begin{split} & \Pr\left(Y_{i,k} > 0 \mid Y_{i,1}, \cdots, Y_{i,k-1}\right) \\ & = \Pr\left(\left(c_{i,k}^P = 0 \land F_{i,h(e_k)} > \lambda_i\right) \lor c_{i,k}^P > 0 \mid Y_{i,1}, \cdots, Y_{i,k-1}\right) \\ & \leqslant \frac{\Pr\left(C_{i,h(e_k)} - 1 > 0 \mid Y_{i,1}, \cdots, Y_{i,k-1}\right)}{+ \Pr\left(F_{i,h(e_k)} > \lambda_i \mid Y_{i,1}, \cdots, Y_{i,k-1}\right)} \\ & \leqslant \frac{E(C_{i,h(e_k)} - 1 \mid Y_{i,1}, \cdots, Y_{i,k-1})}{1} \\ & \leqslant \frac{E(F_{i,h(e_k)} \mid Y_{i,1}, \cdots, Y_{i,k-1})}{\lambda_i} \\ & \leqslant \frac{C_i}{w_i} + \frac{F_i}{\lambda_i w_i}. \end{split}$$

Recall that  $w_i = \lceil \frac{W(R_w - 1)}{R_w^i} \rceil$  and  $\lambda_i = \frac{\Lambda(R_\lambda - 1)}{R_\lambda^i}$ , under the conditions of  $F_i \leqslant \frac{\alpha_i}{\gamma_i}$  and  $C_i \leqslant \frac{\beta_i}{\gamma_i}$ , we have

$$\begin{split} & \operatorname{Pr}\left(X_{i,k}>0 \mid X_{i,1},\cdots,X_{i,k-1}\right) \\ \leqslant & \frac{\beta_i}{\gamma_i w_i} + \frac{2\alpha_i}{\gamma_i \lambda_i w_i} = \frac{4\alpha_i}{\gamma_i \lambda_i w_i} \leqslant \frac{1}{(R_w R_\lambda)^{2^{i-1}+4}} = p_i. \\ & \operatorname{Pr}\left(Y_{i,k}>0 \mid Y_{i,1},\cdots,Y_{i,k-1}\right) \\ \leqslant & \frac{\beta_i}{\gamma_i w_i} + \frac{\alpha_i}{\gamma_i \lambda_i w_i} = \frac{3\alpha_i}{\gamma_i \lambda_i w_i} \leqslant \frac{3}{4(R_w R_\lambda)^{2^{i-1}+4}} \leqslant \frac{3}{4} p_i. \end{split}$$

Theorem A.4. (Theorem 2) Let  $W=\frac{4N(R_wR_\lambda)^6}{\Lambda(R_w-1)(R_\lambda-1)}$ ,  $\alpha_i=\frac{\|F\|_1}{(R_wR_\lambda)^{i-1}}$ ,  $\beta_i=\frac{\alpha_i}{\frac{\lambda_i}{2}}$ ,  $\gamma_i=(R_wR_\lambda)^{(2^{i-1}-1)}$ , and  $p_i=(R_wR_\lambda)^{-(2^{i-1}+4)}$ . Under the conditions of  $F_i\leqslant \frac{\alpha_i}{\gamma_i}$  and  $C_i\leqslant \frac{\beta_i}{\gamma_i}$ , we have

$$\Pr\left(X_i > (1+\Delta)\frac{p_i\alpha_i}{\gamma_i}\right) \leqslant \exp\left(-(\Delta-(e-2))\frac{2p_i\alpha_i}{\lambda_i\gamma_i}\right).$$

and

$$\Pr\left(Y_i > (1+\Delta)\frac{3}{2}\frac{p_i\beta_i}{\gamma_i}\right) \leqslant \exp\left(-(\Delta-(e-2))\frac{3p_i\beta_i}{4\gamma_i}\right).$$

PROOF. According to Theorem A.3,

$$\Pr\left(\frac{X_{i,k}}{\frac{\lambda_i}{2}} = \frac{f_i(e_k)}{\frac{\lambda_i}{2}} \mid \frac{X_{i,1}}{\frac{\lambda_i}{2}}, \cdots, \frac{X_{i,k-1}}{\frac{\lambda_i}{2}}\right) \leqslant p_i.$$

$$\Pr\left(\frac{Y_{i,k}}{2} = 1 \mid \frac{Y_{i,1}}{2}, \cdots, \frac{Y_{i,k-1}}{2}\right) \leqslant \frac{3}{4}p_i.$$

According to Lemma 1,

$$\begin{split} & \operatorname{Pr}\left(X_{i} > (1+\Delta)\frac{p_{i}\alpha_{i}}{\gamma_{i}}\right) \leqslant \operatorname{Pr}\left(X_{i} > (1+\Delta)p_{i}F_{i} \mid F_{i} = \frac{\alpha_{i}}{\gamma_{i}}\right) \\ & = \operatorname{Pr}\left(\sum_{\{e_{k} \in S_{i}^{0}\}} \frac{X_{i,k}}{\frac{\lambda_{i}}{2}} > (1+\Delta)p_{i} \sum_{\{e_{k} \in S_{i}^{0}\}} \frac{f_{i}(e_{k})}{\frac{\lambda_{i}}{2}} \mid F_{i} = \frac{\alpha_{i}}{\gamma_{i}}\right) \\ & \leqslant \exp\left(-(\Delta - (e-2))\frac{\alpha_{i}}{\gamma_{i}\frac{\lambda_{i}}{2}}p_{i}\right) = \exp\left(-(\Delta - (e-2))\frac{2p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right). \\ & \operatorname{Pr}\left(Y_{i} > (1+\Delta)\frac{3}{2}\frac{p_{i}\beta_{i}}{\gamma_{i}}\right) \leqslant \operatorname{Pr}\left(Y_{i} > (1+\Delta)\frac{3}{2}p_{i}C_{i} \mid C_{i} = \frac{\beta_{i}}{\gamma_{i}}\right) \\ & = \operatorname{Pr}\left(\sum_{\{e_{k} \in S_{i}^{1}\}} \frac{Y_{i,k}}{2} > (1+\Delta)\frac{3}{4}p_{i} \sum_{\{e_{k} \in S_{i}^{1}\}} \frac{2}{2} \mid C_{i} = \frac{\beta_{i}}{\gamma_{i}}\right) \\ & \leqslant \exp\left(-(\Delta - (e-2))\frac{\beta_{i}}{\gamma_{i}}\frac{3}{4}p_{i}\right) = \exp\left(-(\Delta - (e-2))\frac{3p_{i}\beta_{i}}{4\gamma_{i}}\right). \end{split}$$

Theorem A.5. (Theorem 3) Let  $R_w R_\lambda \geqslant 2$ ,  $W = \frac{4N(R_w R_\lambda)^6}{\Lambda(R_w - 1)(R_\lambda - 1)}$ ,  $\alpha_i = \frac{\|F\|_1}{(R_w R_\lambda)^{i-1}}$ ,  $\beta_i = \frac{\alpha_i}{\frac{\lambda_i}{2}}$ ,  $\gamma_i = (R_w R_\lambda)^{(2^{i-1}-1)}$ , and  $p_i = (R_w R_\lambda)^{-(2^{i-1}+4)}$ . We have

$$\Pr\left(F_{i+1} > \frac{\alpha_{i+1}}{\gamma_{i+1}} \mid F_i \leqslant \frac{\alpha_i}{\gamma_i} \land C_i \leqslant \frac{\beta_i}{\gamma_i}\right)$$

$$\leqslant \exp\left(-(9-e)\frac{2p_i\alpha_i}{\lambda_i\gamma_i}\right).$$

$$\Pr\left(C_{i+1} > \frac{\beta_{i+1}}{\gamma_{i+1}} \mid F_i \leqslant \frac{\alpha_i}{\gamma_i} \land C_i \leqslant \frac{\beta_i}{\gamma_i}\right)$$

$$\leqslant \exp\left(-(5-e)\frac{2p_i\alpha_i}{\lambda_i\gamma_i}\right) + \exp\left(-(\frac{11}{3}-e)\frac{3p_i\beta_i}{4\gamma_i}\right).$$

PROOF. According to settings, we have

$$\begin{split} p_i \frac{\alpha_i}{\gamma_i} &= \frac{\|F\|_1}{(R_w R_\lambda)^{(2^i + i + 2)}} \leqslant \frac{1}{8} \frac{\alpha_{i+1}}{\gamma_{i+1}} \\ p_i \frac{\beta_i}{\gamma_i} &= p_i \frac{\alpha_i}{\gamma_i \frac{\lambda_i}{2}} \leqslant \frac{1}{8} \frac{\alpha_{i+1}}{\gamma_{i+1} \frac{\lambda_{i+1}}{2}} = \frac{1}{8} \frac{\beta_{i+1}}{\gamma_{i+1}}. \end{split}$$

Recall that  $C_{i+1} = |S_{i+1}^1 \cap S_i^0| + |S_{i+1}^1 \cap S_i^1|$ , and

$$|\mathcal{S}_{i+1}^1 \cap \mathcal{S}_i^0| \leqslant \frac{\sum_{\{e \in \mathcal{S}_i^0 \cap \mathcal{S}_{i+1}\}} f_i(e)}{\frac{\lambda_{i+1}}{2}} \leqslant \frac{X_i}{\frac{\lambda_{i+1}}{2}}$$

Let  $\Gamma_i = \left(F_i \leqslant \frac{\alpha_i}{\gamma_i} \land C_i \leqslant \frac{\beta_i}{\gamma_i}\right)$ , according to Theorem A.1 and Theorem 2,

$$\Pr(F_{i+1} > \frac{\alpha_{i+1}}{\gamma_{i+1}} \mid \Gamma_i) \leqslant \Pr\left(X_i > 8p_i \frac{\alpha_i}{\gamma_i} \mid \Gamma_i\right)$$
$$\leqslant \exp\left(-(9 - e) \frac{2p_i \alpha_i}{\lambda_i \gamma_i}\right).$$

According to Theorem A.2 and Theorem 2,

$$\begin{split} &\Pr(C_{i+1} > \frac{\beta_{i+1}}{\gamma_{i+1}} \mid \Gamma_{i}) \\ &= \Pr(|S_{i+1}^{1} \cap S_{i}^{0}| + |S_{i+1}^{1} \cap S_{i}^{1}| > \frac{\beta_{i+1}}{\gamma_{i+1}} \mid \Gamma_{i}) \\ &\leqslant \Pr(|S_{i+1}^{1} \cap S_{i}^{0}| > \frac{\beta_{i+1}}{2\gamma_{i+1}} \lor |S_{i+1}^{1} \cap S_{i}^{1}| > \frac{\beta_{i+1}}{2\gamma_{i+1}} \mid \Gamma_{i}) \\ &\leqslant \Pr(\frac{X_{i}}{\frac{\lambda_{i+1}}{2}} > \frac{\beta_{i+1}}{2\gamma_{i+1}} \mid \Gamma_{i}) + \Pr(Y_{i} > \frac{\beta_{i+1}}{2\gamma_{i+1}} \mid \Gamma_{i}) \\ &\leqslant \Pr(X_{i} > 4p_{i}\frac{\alpha_{i}}{\gamma_{i}} \mid \Gamma_{i}) + \Pr(Y_{i} > 4p_{i}\frac{\beta_{i}}{\gamma_{i}} \mid \Gamma_{i}) \\ &\leqslant \exp\left(-(5-e)\frac{2p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right) + \exp\left(-(\frac{11}{3}-e)\frac{3p_{i}\beta_{i}}{4\gamma_{i}}\right). \end{split}$$

# A.4 Space and Time Complexity

Theorem A.6. (Theorem 4) Let  $R_w R_\lambda \geqslant 2$ ,  $W = \frac{4N(R_w R_\lambda)^6}{\Lambda(R_w - 1)(R_\lambda - 1)}$ ,  $\alpha_i = \frac{\|F\|_1}{(R_w R_\lambda)^{i-1}}$ ,  $\beta_i = \frac{\alpha_i}{\frac{\lambda_i}{2}}$ ,  $\gamma_i = (R_w R_\lambda)^{(2^{i-1}-1)}$ , and  $p_i = (R_w R_\lambda)^{-(2^{i-1}+4)}$ .

For given  $\Lambda$  and  $\Delta < \frac{1}{4}$ , let d be the root of the following equation

$$\frac{R_{\lambda}^d}{(R_w R_{\lambda})^{(2^d+d)}} = \Delta_1 \frac{\Lambda}{N} \ln(\frac{1}{\Delta}).$$

And use an SpaceSaving of size  $\Delta_2 \ln(\frac{1}{\Lambda})$  (as the (d+1)-layer), then

$$\Pr\left(\forall item \ e, \left| \hat{f}(e) - f(e) \right| \leqslant \Lambda\right) \geqslant 1 - \Delta,$$

where

$$\Delta_1 = 2R_w^2 R_\lambda^2 (R_\lambda - 1), \qquad \Delta_2 = 3 \left( \frac{R_w R_\lambda^2}{R_\lambda - 1} \right) \Delta_1 = 6R_w^3 R_\lambda^4.$$

PROOF. Recall that  $\Gamma_i = \left(F_i \leqslant \frac{\alpha_i}{\gamma_i} \land C_i \leqslant \frac{\beta_i}{\gamma_i}\right)$ , When all conditions  $\Gamma_i$  (including  $\Gamma_{d+1}$ ) are true, we have

$$\begin{split} C_{d+1} \leqslant & \frac{\beta_{d+1}}{\gamma_{d+1}} = \frac{2NR_{\lambda}^{d+1}}{(R_w R_{\lambda})^{(2^d + d - 1)}(R_{\lambda} - 1)\Lambda} = \left(\frac{2R_w R_{\lambda}^2}{R_{\lambda} - 1}\right) \Delta_1 \ln(\frac{1}{\Delta}). \\ F_{d+1} \leqslant & \frac{\alpha_{d+1}}{\gamma_{d+1}} = \frac{\lambda_{d+1}}{2} \frac{\beta_{d+1}}{\gamma_{d+1}} = \lambda_{d+1} \left(\frac{R_w R_{\lambda}^2}{R_{\lambda} - 1}\right) \Delta_1 \ln(\frac{1}{\Delta}). \end{split}$$

Since we use an SpaceSaving of size  $\Delta_2 \ln(\frac{1}{\Delta}) > C_{d+1}$ , it can record all elephant keys without error, and the estimation error for mice keys does not exceed

$$\frac{F_{d+1}}{\Delta_2 \ln(\frac{1}{\Delta}) - C_{d+1}} \leqslant \frac{\lambda_{d+1} \left(\frac{R_w R_\lambda^2}{R_\lambda - 1}\right) \Delta_1 \ln(\frac{1}{\Delta})}{\Delta_2 \ln(\frac{1}{\Delta}) - \left(\frac{2R_w R_\lambda^2}{R_\lambda - 1}\right) \Delta_1 \ln(\frac{1}{\Delta})} = \lambda_{d+1}$$

Therefore, for any item e,

$$\left|\hat{f}(e) - f(e)\right| = \sum_{i=1}^d \lambda_i \leqslant \sum_{i=1}^\infty \frac{\Lambda(R_\lambda - 1)}{R_\lambda^i} = \Lambda$$

Next, we deduce the probability that at least one condition  $\Gamma_i$  is false. Note that

$$\left. \begin{array}{l} \left( \frac{11}{3} - e \right) \frac{3p_i \beta_i}{4\gamma_i} \\ (9 - e) \frac{2p_i \alpha_i}{\lambda_i \gamma_i} \\ (5 - e) \frac{2p_i \alpha_i}{\lambda_i \gamma_i} \end{array} \right\} \geqslant \frac{p_i \alpha_i}{\lambda_i \gamma_i}.$$

Then According to Theorem A.5, we have

$$\Pr\left(\neg\left(\bigwedge_{i=1}^{d}\Gamma_{i+1}\right)\right) = \Pr\left(\bigvee_{i=1}^{d}\neg\Gamma_{i+1}\right) = \Pr\left(\bigvee_{i=1}^{d}\left(\bigwedge_{j=1}^{i}\Gamma_{j} \wedge \neg\Gamma_{i+1}\right)\right)$$

$$\leqslant \sum_{i=1}^{d}\Pr\left(\Gamma_{i} \wedge \neg\Gamma_{i+1}\right) \leqslant \sum_{i=1}^{d}\Pr\left(\neg\Gamma_{i+1} \mid \Gamma_{i}\right)$$

$$\leqslant \sum_{i=1}^{d}\left(\exp\left(-\left(\frac{11}{3} - e\right)\frac{3p_{i}\beta_{i}}{4\gamma_{i}}\right)\right)$$

$$\leqslant \sum_{i=1}^{d}\left(\exp\left(-\left(\frac{11}{3} - e\right)\frac{2p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right) + \exp\left(-\left(5 - e\right)\frac{2p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right)\right)$$

$$\leqslant \sum_{i=1}^{d}3\exp\left(-\frac{p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right).$$

Note that

$$\begin{split} \exp\left(-\frac{p_d\alpha_d}{\lambda_d\gamma_d}\right) &= \exp\left(-\frac{NR_\lambda^d}{(R_wR_\lambda)^{(2^d+d+2)}\Lambda(R_\lambda-1)}\right) \\ &= \exp\left(-\frac{1}{R_w^2R_\lambda^2(R_\lambda-1)}\Delta_1\ln(\frac{1}{\Delta})\right) \\ &= \Delta\left(\frac{1}{R_w^2R_\lambda^2(R_\lambda-1)}\Delta_1\right) = \Delta^2. \end{split}$$

Since  $\Delta \leqslant 1$ , and the monotonicty of  $\exp\left(-\frac{p_d\alpha_d}{\lambda_d\gamma_d}\right)$ , we have

$$\begin{split} \exp\left(-\frac{p_{i}\alpha_{i}}{\lambda_{i}\gamma_{i}}\right) &= \exp\left(-\frac{p_{i+1}\alpha_{i+1}}{\lambda_{i+1}\gamma_{i+1}} \cdot R_{w}^{(2^{i}+1)}R_{\lambda}^{(2^{i})}\right) \\ &\leqslant \exp\left(-\frac{p_{i+1}\alpha_{i+1}}{\lambda_{i+1}\gamma_{i+1}}\right)^{R_{w}R_{\lambda}} \leqslant \exp\left(-\frac{p_{i+1}\alpha_{i+1}}{\lambda_{i+1}\gamma_{i+1}}\right)^{2} \\ &\leqslant \Delta^{2} \exp\left(-\frac{p_{i+1}\alpha_{i+1}}{\lambda_{i+1}\gamma_{i+1}}\right) \end{split}$$

Therefore, we have

$$\sum_{i=1}^{d} 3 \exp\left(-\frac{p_i \alpha_i}{\lambda_i \gamma_i}\right) \leqslant 3 \sum_{i=1}^{d} \Delta^{2i} \leqslant \left(\frac{3\Delta}{1-\Delta^2}\right) \Delta \leqslant \Delta.$$

In other words,

$$\Pr\left(\forall \ item \ e, \left| \hat{f}(e) - f(e) \right| \leqslant \Lambda \right) \geqslant 1 - \Delta,$$

which leads to a weaker conclusion,

$$\forall$$
 item  $e$ ,  $\Pr\left(\left|\hat{f}(e) - f(e)\right| \leqslant \Lambda\right) \geqslant 1 - \Delta$ .

Theorem A.7. Using the same settings as Theorem A.6, the space complexity of the algorithm is  $O(\frac{N}{\Lambda} + \ln(\frac{1}{\Lambda}))$ , and the time complexity of the algorithm is amortized  $O(1 + \Delta \ln \ln(\frac{N}{\Lambda}))$ .

PROOF. Recall that d is the root of the equation

$$\frac{R_{\lambda}^{d}}{(R_{w}R_{\lambda})^{(2^{d}+d)}} = \Delta_{1} \frac{\Lambda}{N} \ln(\frac{1}{\Delta}),$$

which means  $d = O\left(\ln \ln \left(\frac{N}{\Lambda}\right)\right)$ . Therefore, total space used by the data structure is

$$\begin{split} \sum_{i=1}^d w_i + \Delta_1 \ln(\frac{1}{\Delta}) &= \sum_{i=1}^d \lceil \frac{W(R_w - 1)}{R_w^i} \rceil + O(\ln(\frac{1}{\Delta})) \\ &\leq \frac{4N(R_w R_\lambda)^6}{\Lambda(R_w - 1)(R_\lambda - 1)} + d + O(\ln(\frac{1}{\Delta})) \\ &= O(\frac{N}{\Delta} + \ln(\frac{1}{\Delta})) \end{split}$$

Next, we analyze the time complexity. When all condition  $\Gamma_i$  are true, for a new item  $e \notin S_1$ , the probability that it enters the (i+1)-th

layer from the i-th layer is  $\frac{F_i}{\frac{\lambda_2}{N_i}}$  + $C_i$   $\leq p_i$ . Thus the time complexity of insert item e does noes exceed

$$(1 - \Delta) \cdot (1 + \sum_{i=1}^{d} p_i) + \Delta \cdot d = O(1 + \Delta \ln \ln(\frac{N}{\Lambda})).$$