

**Proposition 4.9.** *Let  $D$  be a quantum system and  $\{|x\rangle\}_{x \in \mathcal{X}}$  an orthonormal basis of  $\mathcal{H}_D$  where  $\mathcal{X} = \{0, \dots, d-1\}$ . Consider the unitary matrix  $U_{XD} \in \mathcal{U}(\mathcal{H}_X \otimes \mathcal{H}_D)$ , where  $\mathcal{H}_X = \mathcal{H}_D$ , such that  $U_{XD}|x, y\rangle = |x+y\rangle|y\rangle$  (where the addition is modulo  $d$ ). Then, for any density matrix  $\sigma_{DE} \in \mathcal{D}(\mathcal{H}_D \otimes \mathcal{H}_E)$ , the state*

$$\rho_{XE} = \text{tr}_D((U_{XD} \otimes \mathbb{I}_E)(|0\rangle\langle 0| \otimes \sigma_{DE})(U_{XD} \otimes \mathbb{I}_E)^\dagger)$$

*has classical  $X$ , and  $P_X$  equals the distribution of the outcome of measuring subsystem  $D$  of  $\sigma_{DE}$  in basis  $\{|x\rangle\}_{x \in \mathcal{X}}$  and  $\rho_{E|X=x}$  equals the state to which  $E$  collapses when  $x$  is observed.*

*Proof.* To simplify notation, we skip some of the indices. First, we consider the case of an “empty”  $E$ , i.e.  $\sigma \in \mathcal{D}(\mathcal{H}_D)$ . Due to linearity, it suffices to show the claim for a *pure* state  $\sigma = |\varphi\rangle\langle\varphi|$ , where we can write  $|\varphi\rangle = \sum_x \alpha_x |x\rangle$ . Then,

$$\begin{aligned} \text{tr}_D(U(|0\rangle\langle 0| \otimes \sigma)U^\dagger) &= \sum_{x,y} \alpha_x \bar{\alpha}_y \text{tr}_D(U(|0\rangle\langle 0| \otimes |x\rangle\langle y|)U^\dagger) = \sum_{x,y} \alpha_x \bar{\alpha}_y \text{tr}_D(U|0, x\rangle\langle 0, x|U^\dagger) \\ &= \sum_{x,y} \alpha_x \bar{\alpha}_y \text{tr}_D(|x\rangle\langle x| \otimes |y\rangle\langle y|) = \sum_{x,y} \alpha_x \bar{\alpha}_y \langle y|x\rangle \langle x|y\rangle = \sum_x |\alpha_x|^2 |x\rangle\langle x|. \end{aligned}$$

This is a classical state (with respect to  $\{|x\rangle\}_x$ ), and  $P_X(x) = |\alpha_x|^2$  is the probability of observing  $x$  when measuring  $\sigma$  in basis  $\{|x\rangle\}_x$ .

In case of a composite state  $\sigma \in \mathcal{P}(\mathcal{H}_D \otimes \mathcal{H}_E)$ , it still suffices to show the claim for a *pure* state  $\sigma = |\varphi\rangle\langle\varphi|$ , where now  $|\varphi\rangle = \sum_x \alpha_x |x\rangle|\psi_x\rangle$ . Similar to above, except that  $|\psi_x\rangle\langle\psi_y|$  is carried along, it follows that

$$\rho_{XE} = \sum_x |\alpha_x|^2 |x\rangle\langle x| \otimes |\psi_x\rangle\langle\psi_x|$$

where  $p_x = \sum_{i,j} \alpha_{x,i} \bar{\alpha}_{x,j} = |\sum_i \alpha_{x,i}|^2$  equals the probability to observe  $x$  when measuring the first part of  $\sigma$ , and  $\rho_{E|X=x} = |\psi_x\rangle\langle\psi_x|$  equals the state to which the second part of  $\sigma$  collapses when  $x$  is observed.  $\square$

## 5 Privacy Amplification

In this section we show how a *weak* (or *raw*) key  $X$ , about which an adversary has some but limited quantum information, can be transformed into a *strong* key  $K$  which looks essentially random to the adversary. The transformation is fully public, no secrecy is involved there. Such a process of “amplifying privacy” is called **privacy amplification**. The assumption that the adversary has only *limited* information on the weak key  $X$  will be expressed here by essentially requiring that the size of the adversary’s quantum state, measured in qubits, is smaller than the a priori collision entropy  $H_2(X)$  or the min-entropy  $H_\infty(X)$  of  $X$ ; we refer to Appendix B.5 for the definitions of  $H_2(X)$  and  $H_\infty(X)$  (as well as of the conditional versions).

**Definition 5.1.** *A function  $f : \mathcal{S} \times \mathcal{X} \rightarrow \mathcal{W}$  is called **universal** if*

$$P[f(S, x) = f(S, x')] \leq \frac{1}{|\mathcal{W}|}$$

*for any  $x \neq x' \in \mathcal{X}$  and for  $S$  uniformly distributed over  $\mathcal{S}$ .*

Although a universal function does not have to be hashing, i.e. compressing, they are usually referred to as universal *hash* functions. Examples of universal (hash) functions are

$$f : \{0, 1\}^{\ell \times n} \times \{0, 1\}^n \rightarrow \{0, 1\}^\ell, (A, x) \mapsto Ax$$

with  $\ell \leq n$  and with all operations modulo 2, and

$$f : \{0, 1\}^n \times \{0, 1\}^n \rightarrow \{0, 1\}^\ell, (a, x) \mapsto [a \cdot x]_\ell,$$

with  $\ell \leq n$  and where the multiplication is to be understood as multiplication in  $\mathbb{F}_2^\ell$  and  $[a \cdot x]_\ell$  stands for the first  $\ell$  bits of  $a \cdot x$  with respect to some fixed basis of the  $\mathbb{F}_2$ -vector-space  $\mathbb{F}_2^\ell$ .

**Definition 5.2.** *The **max-entropy** of a state  $\rho \in \mathcal{D}(\mathcal{H})$  is defined as  $H_0(\rho) = \log(\text{rank}(\rho))$ .*

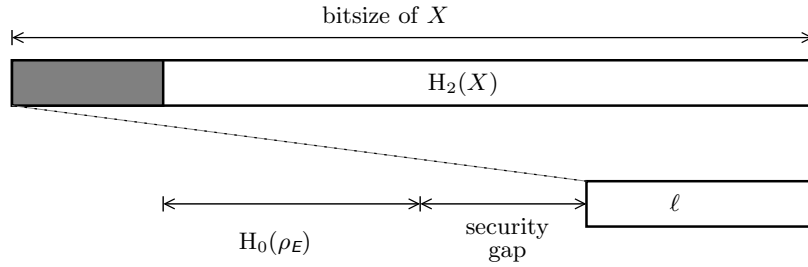
The max-entropy of a state  $\rho_E$  can be used to measure (or at least upper-bound) the entanglement between  $E$  and some, say classical, state  $X$ . In particular, if  $H_0(\rho_E) = 0$ , and thus  $\rho_E$  is pure,  $\rho_{XE}$  must be of the form  $\rho_X \otimes \rho_E$  and hence  $E$  gives no information on  $X$  at all. Clearly, the max-entropy of an  $n$ -qubit state  $\rho$  is bounded by  $H_0(\rho) \leq n$ .

**Theorem 5.3 (Privacy Amplification).** *Let  $X$  be a random variable over  $\mathcal{X}$ , and let  $E$  be a quantum system whose state may depend on  $X$ . Let  $f : \mathcal{S} \times \mathcal{X} \rightarrow \{0, 1\}^\ell$  be a universal hash function and let  $S$  be uniformly distributed over  $\mathcal{S}$  (independent of  $X$  and  $E$ ). Then*

$$\delta(\rho_{f(S,X)SE}, \rho_U \otimes \rho_{SE}) \leq \frac{1}{2} 2^{-\frac{1}{2}(H_2(X) - H_0(\rho_E) - \ell)} \leq \frac{1}{2} 2^{-\frac{1}{2}(H_\infty(X) - H_0(\rho_E) - \ell)}.$$

where  $U$  is uniformly distributed over  $\{0, 1\}^\ell$  (independent of  $X$ ,  $S$  and  $E$ ).

Informally, this means that if  $H_2(X)$  is significantly larger than  $H_0(\rho_E) + \ell$ , the max-entropy of the quantum state plus the size of the hash value, then  $K = f(S, X)$  is essentially random when given  $S$  and the quantum state  $E$ ; see Figure 9.



**Fig. 9.** Size of extractable key.

*Remark 5.4.* With an appropriate definition of the min-entropy  $H_\infty(X|E)$  of a classical  $X$  conditioned on a quantum state  $E$ , one can actually show that  $\delta(\rho_{f(S,X)SE}, \rho_U \otimes \rho_{SE})$  is bounded by  $\frac{1}{2} 2^{-\frac{1}{2}(H_\infty(\rho_{XE|E}) - \ell)}$ . Theorem 5.3 is then a simple corollary, since  $H_\infty(X|E) \geq H_\infty(X) - H_0(\rho_E)$ . However, the proof is significantly more involved.

In the proof, we will actually consider the (square of the) **Hilbert-Schmidt distance**: for two density matrices  $\rho$  and  $\sigma$  in  $\mathcal{D}(\mathcal{H})$  define  $\Delta(\rho, \sigma) := \text{tr}((\rho - \sigma)^2)$ , i.e., the sum of the squares of the eigenvalues of  $\rho - \sigma$ . The following lemma shows that an upper bound on the (square of the) Hilbert-Schmidt distance translates to an upper bound on the trace norm distance.

**Lemma 5.5.** *For any density matrices  $\rho, \sigma \in \mathcal{D}(\mathcal{H})$ :  $\delta(\rho, \sigma) \leq \frac{1}{2} \sqrt{\text{rank}(\rho - \sigma) \Delta(\rho, \sigma)}$ .*

*Proof.* Let  $r = \text{rank}(\rho - \sigma)$ . We may assume that  $\rho - \sigma$  is diagonal with the eigenvalues  $\lambda_1, \dots, \lambda_r, 0, \dots, 0$  on its diagonal. It now follows that

$$2\delta(\rho, \sigma) = \sum_i |\lambda_i| = r \sum_i \frac{1}{r} \sqrt{\lambda_i^2} \leq r \sqrt{\sum_i \frac{1}{r} \lambda_i^2} = \sqrt{r \sum_i \lambda_i^2} = \sqrt{r \Delta(\rho, \sigma)}$$

where the inequality is Jensen's inequality (Proposition B.4).  $\square$

*Proof (of Theorem 5.3).* By Lemma 4.8 and using the fact that  $S, U$  and  $E$  are all independent,

$$\begin{aligned} \delta(\rho_{f(S,X)SE}, \rho_U \otimes \rho_E) &= E_{s \leftarrow S} [\delta(\rho_{f(S,X)E|S=s}, \rho_U \otimes \rho_{E|S=s})] = E_{s \leftarrow S} [\delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E)] \\ &\leq \frac{1}{2} 2^{\frac{1}{2}(\ell + H_0(\rho_E))} E_{s \leftarrow S} \left[ \sqrt{\Delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E)} \right] \leq \frac{1}{2} 2^{\frac{1}{2}(\ell + H_0(\rho_E))} \sqrt{E_{s \leftarrow S} [\Delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E)]}, \end{aligned}$$

where the inequalities follow from Lemma 5.5 and Jensen's inequality (Proposition B.4). It thus suffices to show that  $E_{s \leftarrow S} [\Delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E)] \leq 2^{-H_2(X)}$ .

Let  $s$  be a fixed value in  $\mathcal{S}$ . Writing  $W = f(s, X)$ , we can re-write the square of the Hilbert-Schmidt distance as follows.

$$\begin{aligned} \Delta(\rho_{WE}, \rho_U \otimes \rho_E) &= \text{tr} \left( \left( \sum_w P_W(w) |w\rangle\langle w| \otimes \rho_E^w - 2^{-\ell} \sum_w |w\rangle\langle w| \otimes \rho_E \right)^2 \right) \\ &= \text{tr} \left( \left( \sum_w |w\rangle\langle w| \otimes (P_W(w) \rho_E^w - 2^{-\ell} \rho_E) \right)^2 \right) \\ &= \text{tr} \left( \sum_w (P_W(w) \rho_E^w - 2^{-\ell} \rho_E)^2 \right) \\ &= \text{tr} \left( \sum_w (P_W(w)^2 (\rho_E^w)^2 - 2P_W(w) 2^{-\ell} \rho_E^w \rho_E + 2^{-2\ell} \rho_E^2) \right) \\ &= \text{tr} \left( \sum_w P_W(w)^2 (\rho_E^w)^2 - 2^{-\ell} \rho_E^2 \right) \end{aligned}$$

where the third equality follows from the fact that the matrix at hand is in block-diagonal form. Plugging in  $f(s, X)$  for  $W$  and using linearity of the trace, we thus get

$$\Delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E) = \text{tr} \left( \sum_w P_{f(s,X)}(w)^2 (\rho_E^w)^2 \right) - \text{tr} \left( 2^{-\ell} \rho_E^2 \right).$$

Now note that

$$\begin{aligned} \text{tr} \left( \sum_w P_{f(s,X)}(w)^2 (\rho_E^w)^2 \right) &= \text{tr} \left( \sum_w \left( \sum_{x: f(s,x)=w} P_X(x) \rho_E^x \right) \left( \sum_{x': f(s,x')=w} P_X(x') \rho_E^{x'} \right) \right) \\ &= \text{tr} \left( \sum_{x,x'} P_X(x) P_X(x') \delta_{f(s,x), f(s,x')} \rho_x \rho_{x'} \right) = \sum_{x,x'} P_X(x) P_X(x') \delta_{f(s,x), f(s,x')} \text{tr}(\rho_E^x \rho_E^{x'}) \end{aligned}$$

where  $\delta_{w,w'}$  is the Kronecker Delta with  $\delta_{w,w'} = 1$  if  $w = w'$  and 0 otherwise, and

$$\text{tr} \left( 2^{-\ell} \rho_E^2 \right) = \text{tr} \left( 2^{-\ell} \left( \sum_x P_X(x) \rho_E^x \right)^2 \right) = \sum_{x,x'} P_X(x) P_X(x') 2^{-\ell} \text{tr}(\rho_E^x \rho_E^{x'})$$

Using that due to the universal property  $E_{s \leftarrow S} [\delta_{f(s,x), f(s,x')}] = P[f(S, x) = f(S, x')] \leq 2^{-\ell}$  for all  $x \neq x'$ , and using that  $0 \leq \text{tr}(\rho_E^x \rho_E^{x'}) \leq 1$  and  $0 \leq \text{tr}(\rho_E^x \rho_E^{x'})$ , it follows that

$$E_{s \leftarrow S} [\Delta(\rho_{f(s,X)E}, \rho_U \otimes \rho_E)] = \sum_{x,x'} P_X(x) P_X(x') (E_{s \leftarrow S} [\delta_{f(s,x), f(s,x')}] - 2^{-\ell}) \text{tr}(\rho_E^x \rho_E^{x'})$$

$$\leq \sum_x P_X(x)^2 \text{tr}(\rho_x^2) \leq \sum_x P_X(x)^2 = 2^{-H_2(X)},$$

which was to be shown.  $\square$

The proof of the following is given as an exercise.

**Corollary 5.6.** *Let  $X$  be a random variable over  $\mathcal{X}$ , let  $Y$  be a random variable over  $\mathcal{Y}$ , and let  $E$  be a quantum system whose state may depend on  $X$  and  $Y$ . Let  $f : \mathcal{S} \times \mathcal{X} \rightarrow \{0, 1\}^\ell$  be a universal hash function and let  $S$  be uniformly distributed over  $\mathcal{S}$  (independent of  $X, Y$  and  $E$ ). Then*

$$\delta(\rho_{f(S,X)SE}, \rho_U \otimes \rho_{SE}) \leq \frac{1}{2} 2^{-\frac{1}{2}(H_2(X|Y) - H_0(\rho_E) - \ell)} \leq \frac{1}{2} 2^{-\frac{1}{2}(H_\infty(X|Y) - H_0(\rho_E) - \ell)},$$

where  $U$  is uniformly distributed over  $\{0, 1\}^\ell$  (independent of  $X, S$  and  $E$ ).

## 6 Subset Sampling – Classical and Quantum

The **Hamming weight**  $W(x)$  of a bit-string  $x = (x_1, \dots, x_m) \in \{0, 1\}^m$  is defined to be the number of 1's occurring within  $x$ . Similarly, the **relative Hamming weight**  $\omega(x)$  of  $x$  is given by its Hamming weight divided by its bit-length  $m$ :  $\omega(x) = W(x)/m$ . We say that the relative Hamming weight of  $x$  is  $\varepsilon$ -close to  $\beta \in \mathbb{R}$ , denoted as  $\omega(x) \approx_\varepsilon \beta$ , if  $|\omega(x) - \beta| \leq \varepsilon$ . For any subset  $T \subseteq \{1, \dots, m\}$  of size  $k$ , we write  $x_T$  for the restriction of  $x$  to the positions in  $T$ :  $x_T = (x_i)_{i \in T} \in \{0, 1\}^k$ .

Consider the following problem: we want to *estimate* the (relative) Hamming weight of an unknown but fixed string  $x \in \{0, 1\}^m$  (of known bit-length  $m$ ) by only looking at a small number of positions in  $x$ . A canonical way to do so is as follows: choose at random a sample subset  $T \subset \{1, \dots, m\}$  of linear size (i.e. size  $\alpha m$  for some constant  $0 < \alpha < 1$ ), and take  $\omega(x_T)$  as estimate for  $\omega(x)$ . Very generally, we allow the following kinds of sampling strategies: choose a sample subset  $T \subset \{1, \dots, m\}$  according to *some* fixed probability distribution  $P_T$ , and compute the estimate for  $\omega(x)$  as *some* (possibly randomized) function of  $x_T$ .

**Definition 6.1.** *A sampling strategy consists of a triple  $\Sigma = (P_T, P_S, estim)$ , where  $P_T$  is a distribution over the subsets of  $\{1, \dots, m\}$ ,  $P_S$  is a (independent) distribution over a finite set  $\mathcal{S}$ , and  $estim$  is a function  $estim : \mathcal{S} \times \{(t, v) : t \subseteq [n], v \in \{0, 1\}^{|t|}\} \rightarrow \mathbb{R}$ .*

We want to measure the reliability of such a general estimation strategy, i.e., how well it predicts the (relative) Hamming weight of the string  $x$ . Actually, for technical reasons (and because the positions within the sample subset  $T$  are anyway revealed), we want to measure how well such a general strategy predicts the (relative) Hamming weight of  $x_{\bar{T}} \in \{0, 1\}^n$  (where  $n = m - |T|$ ), i.e., of  $x$  restricted to the positions  $\bar{T} = \{1, \dots, m\} \setminus T$  outside of the sample  $T$  (see Figure 10, top).

**Definition 6.2.** *For any  $\varepsilon > 0$ , we define the error probability*

$$err_\varepsilon(\Sigma) := \max_{x \in \{0, 1\}^m} P[\omega(x_{\bar{T}}) \not\approx_\varepsilon estim(S, T, x_T)]$$

where the probability is over the choices of  $T$  and  $S$  according to  $P_{TS} = P_T P_S$ .

By definition, for any choice of  $x \in \{0, 1\}^m$ :  $\omega(x_{\bar{T}}) \approx_\varepsilon estim(S, T, x_T)$  except with probability at most  $err_\varepsilon(\Sigma)$ . Using classical sampling theory (see e.g. [?]), one can e.g. show that for