• Continuous pdf:

$$f_X(x): \mathcal{X} \to [0, \infty), f_X(x) = \lim_{\epsilon \to 0} \frac{1}{\epsilon} \cdot \Pr[x \le X \le x + \epsilon]$$

• Continuous cdf:

$$F_x(x) := \Pr[X \le x]$$
 where $\Pr[a \le X \le b] = \int_a^b f_x(x) dx$

• Uniform distribution on $\mathcal{X} = [u, v]$:

$$f_X(x) = 1/(v-u)$$
 for $x \in \mathcal{X}$

• Normal distribution:

$$f_X(x) = (2\pi)^{-1/2} \exp(-x^2/2)$$

• Dirac delta property:

$$\int_{-\infty}^{\infty} \mathrm{d}x \, b(x) \delta(x-a) = b(a)$$

• Expectation value of g(X) where $X \in \mathcal{X}$:

$$\mathbb{E}[g(X)] = \sum_{x \in \mathcal{X}} \Pr[X = x] g(x)$$
 , k'th moment of $X = \mathbb{E}[X^k]$

• Statistical distance of $X, Y \in \mathcal{X}$:

$$\Delta(X,Y) = \frac{1}{2} \sum_{x \in \mathcal{X}} |\mathbb{P}(x) - \mathbb{Q}(x)|$$

• Covariance matrix *K*:

$$K_{i,j} = \mathbb{E}[X_i X_j] - \mathbb{E}[X_i] \cdot \mathbb{E}[X_j]$$

Zero covariance ($K_{1,2} = K_{2,1} = 0$) does not imply X_1 and X_2 are independent.

• Marginal distribution for *X* when $(X, Y) \sim \mathbb{P}$:

$$\Pr[X = x] = \sum_{y} \mathbb{P}(x, y)$$

• Conditional probability for $(X, Y) \sim \mathbb{P}$:

$$\Pr[X = x | Y = y] = \frac{\Pr[X = x, Y = y]}{\Pr[Y = y]} = \frac{\mathbb{P}(x, y)}{\mathbb{P}_2(y)}$$

- (Shannon) Entropy rules:
 - 1. **Additivity**: inf of a set of indep. RVs must be the sum of indiv. inf. contents
 - 2. Sub-additivity: Total inf. content of two jointly distrib. RVs cannot exceed sum of seperate infs.
 - 3. Expansibility: Adding extra outcome of prob. 0 does not affect
 - 4. **Normalization**: The distrib (1/2, 1/2) has inf. of 1 bit.
 - 5. The distrib (p, 1-p) for $p \to 0$ has zero inf.

• Shannon entropy:

$$H(X) = \sum_{x \in \mathcal{X}} p_x \log_2 \frac{1}{p_x}$$

• Binary entropy function: 2 outcomes with prob.
$$p$$
 and $1-p$: $h(p) = p \log \frac{1}{p} + (1-p) \log \frac{1}{1-p}$

• Differential entropy for continuous RV $X \sim \rho$:

$$h_{\text{diff}}(X) = -\int dx \, \rho(x) \log \rho(x) = \mathbb{E}_x \log \frac{1}{\rho(x)}$$

• Relative entropy (Kullback-Leibler distance):

$$D(\mathbb{P}||\mathbb{Q}) = \sum_{x \in \mathcal{X}} \mathbb{P}(x) \log \frac{\mathbb{P}(x)}{\mathbb{Q}(x)}$$

• Entropy of jointly distrib. RVs: H(X,Y) or H(XY):

$$H(X,Y) = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p_{xy} \log \frac{1}{p_{xy}}$$

• Conditional entropy:

$$\begin{array}{l} H(X|Y) = \mathbb{E}_y[H(X|Y=y)] = -\sum_{x \in \mathcal{X}} p_x \sum_{y \in \mathcal{Y}} p_{x|y} \log p_{x|y} \\ H(X|Y) = H(X,Y) - H(Y) \end{array}$$

• Mutual information:

$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

$$\mathbf{I}(X;Y) = H(X,Y) - H(X|Y) - H(Y|X)$$

$$\mathbf{I}(X;Y) = H(X) + H(Y) - H(X,Y)$$

$$\mathbf{I}(X;Y|Z) = \mathbb{E}_z \mathbf{I}(X|Z=z;Y|Z=z)$$

• Min entropy:

$$H_{\min}(X) = -\log \max_{x \in \mathcal{X}} p_x = -\log p_{\max}$$

$$H_{\min}(X|Y) = -\log \mathbb{E}_y \max_{x \in \mathcal{X}} p_{x|y}$$

$$H_{\min}(X|Y) = -\log \mathbb{E}_y \max_{x \in \mathcal{X}} p_{x|y}$$

• Linear binary codes:

Maps k-bit msg x to n-bit (n > k) codeword $c_x \in \mathcal{C}$. Perceived string $z = c_z \oplus e$. Minimum distance of code: d = $\min_{c,c'\in\mathcal{C}}$ HammingWeight $(c\oplus c')$. Receiver determines which $c_{\hat{x}}$ is closest to z and decodes it into \hat{x} . Error correcting capability $t = \lfloor \frac{d-1}{2} \rfloor$.

• Generator (G is $k \times n$) and parity check (H is $(n - k) \times n$) matrix: $c_x = xG$. $G = (\mathbf{1}_k | A)$. $H = (-A^T | \mathbf{1}_{n-k})$. $GH^T = 0$, $cH^t = 0$. All k rows of G are linearly independent.

• Syndrome decoding $(s(z) \in \{0,1\}^{n-k})$: $s(z) = zH^T = (c_x + e)H^T = eH^T$

Syndrome depends only on the error pattern, not on the message.

ullet Hamming bound: Binary code of length n that can correct t errors: $2^k \le 2^n / \sum_{i=0}^t \binom{n}{i}$. Approx $\log n$ bits of redundancy per bit error.

• Channel capacity:

Inf. content error free: $k \leq \mathbf{I}(C; Z)$ BSC capacity (per bit): $\frac{k}{n} \leq \mathbf{I}(C_j; Z_j) = H(Z_j) - H(Z_j|C_j)$ This is called the BSC code rate: BSC CODE RATE $\leq 1 - h(\epsilon)$ Following the rule of thumb: $h(\epsilon) = -\epsilon \log \epsilon + \mathcal{O}(\epsilon)$

 Uniformly random bits from continuous source: **TODO**

The von Neumann alg:

Given (b_1, b_2) , if $b_1 = b_2$ then no output, else output b_1 .

• Piling-up lemma:

Let $X_1,...,X_n \in \{0,1\}$ be independent with biases $\Pr[X_i = 1]$ – $\Pr[X_i = 0] = \alpha_i$. Construct $Y = X_1 \oplus X_2 \oplus ... \oplus X_n$. The bias of Yis $\Pr[Y=1] - \Pr[Y=0] = (-1)^{n-1} \prod_{i=1}^n \alpha_i$. Thus by xoring many bits together the bias gets reduced.

• Resilient function:

A function $\Psi:\{0,1\}^n \to \{0,1\}^m$ is (n,m,t)-resilient of, for any tcoords $i_1,...,i_t \in [n]$, any $a_1,...,a_t \in \{0,1\}$ and any $y \in \{0,1\}^m$ it holds that: $\Pr[\Psi(X) = y | x_{i_1} = a_1, ..., x_{i_t} = a_t] = 2^{-m}$ i.e.: Knowledge of t values of the input does not give inf. that would help in guessing the output. ECC example ([n, k, d] code): $\Psi: \{0,1\}^n \to \{0,1\}^k$. $\Psi = xG^T$. Then Ψ is an (n,k,d-1)-resilient fun.

• Strong extractor Ext : $\{0,1\}^n \times \{0,1\}^* \to \{0,1\}^l$: Takes n-bit string X and randomness R and outputs an l-bit string (l < n). Z = Ext(X, R). Ext is a strong extractor for source minentropy m, output length l and nonuniformity ϵ if for all distrib of X with $H_{\infty}(X) \geq m$ it holds that $\Delta(ZR; U_lR) \leq \epsilon$.

- Universal hash functions:
- Leftover hash lemma:
- Binary symmetric channel:
- Secret capacity:
- PUF types and their properties:
- PUF applications + attack models:
- PUF entropy and inf. stuff:
- Fuzzy extractor definition:
- When to use FE and SS:
- Zero leakage scheme stuff:
- Helper data scheme:
- Distance bounding principles (and fraud types):
- Brands-chaum protocol:

- Swiss knife protocol
- Analog impl.:
- Quantum stuff: