

Information Transmission in Brief

Term	Discrete Random Variables (DRV) System	Continues Random Variables (CRV) System
Self-Information	$I_{x_i} = -\text{Log}_b p(x_i)$ b-unit of information	$I_{x_i} = -\text{Log}_b f(x)$ b-unit of information
Information Units	For b=10 (Hartley unit), b=e (natural unit or Nat.), and the most common base is b=2 (Bit). For unit conversion ($Z_{\text{bits}} = \text{Log}_z / \text{Log}_2 = \text{Ln}_z / \text{Ln}_2$)	
Source Entropy	$H(x) = E[I_{x_i}] = \overline{I_{x_i}} = - \sum_x P(x_i) \text{Log} P(x_i)$	$H(x) = E[I_{x_i}] = \overline{I_{x_i}} = - \int_{-\infty}^{\infty} f(x) \cdot \text{Log} f(x) dx$
Mutual Information	$I_{x:y} = I_x - I_{x y} = -\text{Log} p(x) + \text{Log} p(x y) = \text{Log} \frac{p(x y)}{p(x)}$	$I_{x:y} = I_x - I_{x y} = -\text{Log} f(x) + \text{Log} f(x y) = \text{Log} \frac{f(x y)}{f(x)}$
	$I_{x:y} = I_y - I_{y x} = -\text{Log} p(y) + \text{Log} p(y x) = \text{Log} \frac{p(y x)}{p(y)}$	$I_{x:y} = I_y - I_{y x} = -\text{Log} f(y) + \text{Log} f(y x) = \text{Log} \frac{f(y x)}{f(y)}$
Average Mutual Information	$I = \sum_y \sum_x P(x_i, y_j) \text{Log} \frac{p(x_i y_j)}{p(x_i)} = \sum_y \sum_x P(x_i, y_j) \text{Log} \frac{p(y_j x_i)}{p(y_j)}$	$I = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \text{Log} \frac{f(x y)}{f(x)} dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \text{Log} \frac{f(x y)}{f(x)} dx dy$
Receiver Entropy	$H(y) = - \sum_y P(y_j) \text{Log} P(y_j)$	$H(x) = - \int_{-\infty}^{\infty} f(y) \cdot \text{Log} f(y) dy$
Conditional Entropies	Noise $H(y x) = - \sum_x \sum_y P(x_i, y_j) \text{Log} P(y_j x_i)$	$H(y x) = - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \text{Log} f(y x) dx dy$
	Losses $H(x y) = - \sum_x \sum_y P(x_i, y_j) \text{Log} P(x_j y_i)$	$H(x y) = - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \text{Log} f(x y) dx dy$
Joint or System Entropy	$H(x, y) = - \sum_x \sum_y P(x_i, y_j) \text{Log} P(x_i, y_j)$	$H(x, y) = - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \text{Log} f(x, y) dx dy$
Useful Relations (Prove them?)	$I = H(y) - H(y x)$, $H(x, y) = H(x) + H(y x)$, $H(x, y) = I + H(y x) + H(x y)$ The units for all H and I are bit/symbol $I = H(x) - H(x y)$, $H(x, y) = H(y) + H(x y)$, $H(x, y) = H(x) + H(y) - I$	
Noiseless Channel	$P(y_j x_i) = P(x_j y_i) = 1$ for i=j then $H(y x) = H(x y) = 0$ and $H(x) = H(y) = H(x, y) = I$ $= 0$ for i≠j (no error in the channel)	
Maximum source entropy	$H_{\text{max}}(x) = \text{Log} M$, with $P(x_i) = 1/M$, for all x_i M= No. of source symbols	$H_{\text{max}}(x) = \text{log} \sqrt{2\pi e \sigma^2}$, with $f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-(x-\bar{x})^2 / 2\sigma^2}$ (i.e the pdf of CRV is Gaussian or Normal)
Source efficiency	$\eta = (H(x) / H_{\text{max}}(x)) \cdot 100\%$ and Redundancy = $(1 - \eta) \cdot 100\%$, (both H(x) and H_{max} should have the same units)	
Capacity of channel	For symmetric, where the rows contents of p(y x) matrix are the same $C = I_{\text{max}} = H_{\text{max}}(y) - H_{y x}$ with $H_{\text{max}}(y) = \text{Log} N$ and N= No. of received symbols and $H(y x) = - \sum_y P(y_j x_i) \text{Log} P(y_j x_i)$ For non-symmetric channel, one should derive $I = f(p(x_i))$ with respect to source symbol probabilities {p(x _i)} to find {p _m (x _i)}	Assumptions : Source and noise are: Gaussian with zero means, the channel is additive (i.e. AWGN), S=signal power, N=Noise Power, B=channel Bandwidth, N _o =One sided power spectral density of AWGN $C = \text{Log}_2(1 + S/N)$ bit/symbol $C_r = 2 \cdot B \cdot C$ $C_r = B \cdot \text{Log}_2(1 + S/N)$ bit/sec(bps) $C_r = B \cdot \text{Log}_2(1 + S/B \cdot N_o)$
Channel efficiency and redundancy	$\eta = (I/C) \cdot 100\%$ Redundancy = $(1 - \eta) \cdot 100\%$	Spectral Efficiency = $C_r/B = \text{Log}_2(1 + S/N)$ (bit/sec/Hz) $\eta = (\text{Actual Rate} / C_r) \cdot 100\%$ Redundancy = $(1 - \eta) \cdot 100\%$