Source Coding _

Introduction Diagram of a general communication system. Discrete sources output of the source is in discrete time and discrete valued. Source Coding representation of information sources in bits. Source Code Function $C: U \mapsto \{0,1\}^* = \{\emptyset,0,1,00,\ldots\}$. Non-Singular Codes A code C is singular if $\exists u \neq v/C(u) = C(v)$. A code C is non-singular if it is not singular. With a code C define for a positive integer $n: C^n: U^n \mapsto \{0,1\}^*$ as $C^n(u_1,u_2,...,u_n) = C(u_1)C(u_2)...C(u_n)$ $C^*: U^* \mapsto \{0,1\}^*$ as $C^*(u_1u_2...u_n) = C(u_1)C(u_2)...C(u_n)$ Uniquely Decodable Codes A code C is said to be uniquals decodable if C^* is non-singular.We want our codes to be uniquals decodable.

Prefix-Free Codes A sequence $u_1,...u_n$ is a prefix of $v_1,...,v_n$ if $n\geqslant m/$ $u_1=v_1,...,u_m=v_m$. A code C is said to be prefix-free if $\forall u\neq v$ C(u) is not a prefix of C(v).

Theorem A prefix-free code is uniquely decodable. (In a binary-tree representation of a PF code all codewords are found on the leaves).

Kraft's Inequality for PF Codes Theorem If C is PF then $Kraftsum(C) \triangleq \sum_{u \in U} 2^{-length(C(u))} \leq 1$. $Proposition \ Kraftsum(C^n) = [Kraftsum(C)]^n$. Kraft's Inequality for extensions of codes Proposition Suppose $C: U \mapsto \{0,1\}^*$ is a non-singular code then $Kraftsum(C) = \sum_{u \in U} 2^{-length(C(u))} \leq 1 + max \ [length(C(u))]$

Kraft's Inequality for uniquely decodable codes Theorem If C is a uniquely decodable code then $Kraftsum(C) \leq 1$. Corollary If C is a uniquely decodable code then there exists a PF code C' such that length(C(u)) = length(C'(u)).

Reverse Kraft's inequality $\it{Theorem}$ Given an alphabet \it{U} and a function

then there exist a PF code $C: U \mapsto \{0,1,2,3,\ldots\}/\sum_{u \in U} 2^{-length(C(u))} \leq 1$ then there exist a PF code $C: U \mapsto \{0,1\}^*/ \ \forall u \in U$ length(C(u)) = l(u)

Sources A source producer a sequence u_1,u_2,u_3,\ldots each $u_i\in U$ being random variables. A *memory-less* source is one where u_1,u_2,\ldots are independent. A *stationary* source is one where each (u_i,\ldots,u_{i+n-1}) has the same statistics as (u_1,\ldots,u_n) for each i and each i. A memory-less and stationary source is equivalent to u_1,u_2,\ldots are independent, identically distributed (iid).

Expected codeword length $E\left[length(C(u))\right]$ average number of bits/letter the code uses to represent the source. We want to minimize it and C to be uniquely decodable.

Entropy

Lemma $ln(z) \le z^{-1}$ with eq if z=1. Property 0 < H(U) < loq |U|

Entropy as a lower-bound to the expected codeword length *Theorem* For any uniquely decodable code Cfor a source U, we have $E\left[length(C(u))\right] \ge \sum_{u} p(u)log_2 \frac{1}{p(u)} \triangleq H(u)$ Existence of PF codes with average length at most entropy + 1 Theorem Given source U there exists a PF code C s.t. E[length(C(u))] > H(u) + 1Entropy of multiple random variables Property Suppose U and V are ind. RV. Then H(UV) = H(U) + H(V). Observe Suppose we have $U_1U_2...$ iid. If we use a code C to represent n letters at time., we will have $H(U_1...U_n) <$ $E[length(C(U_1...U_n))] < H(U_1...U_n) + 1$. Also $\frac{1}{n}H(U_1...U_n) = H(U_1)$ (iid of U). Properties of optimal codes 1 If p(u) < p(v) then l(u) > l(v). 2 In an optimal PF code there are more than 2 longest codewords. If not the longest codeword can be shortered without violating the PF condition. 3 Among optimal codes, there is one for the two least probable symbols are siblings. Huffman procedure Procedure to design the optimal code. 1 Given prob $p_1, p_2, ..., p_{k-1}, p_k$. Start with the two smallest prob. 2 Group them together as the binary descendant of a node. 3 Repeat until one node is left.

Equivalence of PF codes and strategy for guessing via binary questions TODO

Interpretation of entropy as expected number of questions for guessing the random variable TODO

Mutual Information

Conditional Entropy and Mutual Information Conditional Entropy $H(U|V=v) = \sum_{u} p(u|v) log \frac{1}{p(u|v)}$

 $\begin{array}{l} H(UV) = H(U) + H(V|U) = H(V) + H(U|V) \\ Theorem \ H(U_1...U_n) = \\ H(U_1) + H(U_2|U_1) + ... + H(U_n|U_1...U_{n-1}) \\ Theorem \\ I(U_1...U_n,V) = I(U_1;V) + ... + I(U_n;V|U_1...U_{n-1}) \\ \text{Review of Markov Chain Suppose } X,Y,Z \text{ are RVs.} \\ \text{We can write } p(xyz) = p(x)p(y|x)p(z|xy). \text{ Because} \end{array}$

 $p(y|x) = \frac{p(xy)}{p(x)}$. If X - Y - Z then p(xyz) = p(x)p(y|x)p(z|y). Suppose $U_1 - U_2 - ... - U_n$ then $H(U_1...U_n) = H(U_1) + H(U_2|U_1) + ... + H(U_n|U_{n-1})$ Data Processing Inequality Theorem Suppose U-V-W then $I(U;W) \leq I(U;V)$ Corollary If U-V-W then I(U;W) < I(V;W). Corollary If U - V - W - X then $I(U; X) \leq I(V; W)$. I(UV;W) = I(U;W) + I(V;W|U) =I(V;W) + I(U;W|V). Entropy Rate Given a stochastic process $U_1, U_2...$ we define its entropy rate $H(U) = \lim_{n \to \infty} \frac{1}{n} H(u_1...u_n)$ if the limit exists. Entropy Rate of Stationary Processes Theorem If u_1, u_2, \dots is stationary process, then the entropy rate exists and $\lim_{n\to\infty} \frac{1}{n} H(u_1...u_n) = \lim_{n\to\infty} H(u_n|u_1...u_{n-1})$ Coding Theorem for Stationary Sources Theorem If U_1, U_2, \dots is a stationary process with entropy rate H, then $\forall \varepsilon > 0$ there exists a source code $C_n:U^n\to\{0,1\}^*$ s.t. the average code length is less than $H + \varepsilon$ Fixed-to-Fixed Length Source Codes Codes of type $U \to \{0,1\}^*$ or $U^n \to \{0,1\}^*$ are called fixed-to-variable length codes, and all our designs

have error free recovery of the source from its representation. We want Fixed-to-fixed codes $C:U^n \rightarrow \{0,1\}^k \ (2^k \ \text{representations}),$ to obtain efficient codes we will give up error free recovery replace this by recovery with very small prob. of error. The code assign binary representations only to a subset $S \subset U^n$ which ensure

 $Pr((u_1...u_n) \in S) \approx 1 \text{ and } |S| \leq 2^k.$

______ Typicality _

Typicality Given an alphabet U and distribution p in U. We have a source that produces iid letters u_i with distribution p. We want a $set \ T_{n,\varepsilon} \subset U^n$. Properties of Typical Sets 1.

$$Pr((u_1...u_n) \in T_{n,\varepsilon,p}) \approx 1 \ (\geq 1 - \frac{|U|}{n\varepsilon^2 p(u)}). \ 2.$$

 $|T_{n,\varepsilon,p}| \leq 2^{n(1+\varepsilon)H(u)}$

Asymptotic Equipartition Property Def AEP is a general property of the output samples of a stochastic source. It is fundamental to the concept of typical set used in theories of compression. Theorem If $U_1,...U_n$ iid $\sim q$ and $(u_1...u_n) \in T_{n,\varepsilon,p}$ then $Pr((U_1...U_n) = (u_1...u_n)) = \prod_{i=1}^n q(u_i)$. Corollary $Pr(((U_1...U_n) = (u_1...u_n)) \in T_{n,\varepsilon,p}) = 2^{-n(1\pm\varepsilon)D(p||q_1)2\pm n\varepsilon H(p)}(1\pm\varepsilon) \stackrel{?}{=} 2^{-nD(p||q_1)}$. Consequently If $(X_1,Y_1)...(X_n,Y_n)$ iid p_Xp_Y then $Pr(((X_1,Y_1)...(X_n,Y_n)) \in T_{n,\varepsilon,p_{XY}}) \stackrel{?}{=} 2^{-nI(X;Y)}$ Source Coding by AEP 1. Assign to every member of $T_{n,\varepsilon,p}$ a distinct element of $\{0,1\}^*$. Call this $C:T_{n,\varepsilon,p} \to \{0,1\}^*$. 2. The source code is the following :Observe if $(U_1...U_n) \in T_{n,\varepsilon,p}$ represent it by 0 else by 1.

Variable-to-Fixed Length Source Codes \equiv Dual of Fixed-to-Variable length source coding \equiv Dictionary to sed source coding ldea Given an alphabet U, find a dictionary $D \subset U^*$, assign $\lceil log|D| \rceil$ bit binary representation to words in D, and then given $U_1U_2...$, parse it into $w_1, w_2...$ of dictionary words and represent each words by its binary description. Valid and Prefix-Free Dictionaries The words of valid and PF dictionaries form the leaves of a complete dictionary tree.

Relationship between word- and letter-entropies for valid, prefix-free dictionaries nbr of bits/letter $=\frac{m \lceil \log |D| \rceil}{length(W_1)+...+length(W_m)} \to \frac{\lceil \log |D| \rceil}{E \lceil length(W_1) \rceil}$ Lemma Suppose Z is non negative integer valued RV. Then $E[Z] = \sum_{n=0}^{\infty} Pr[Z>n]$. Observation nbr of words = nbr of leaves in tree representation = 1 + (|U| - 1) (nbr interior nodes).

Tunstall procedure

Tunstall procedure 1. D=U with |U| words and one interior node (root). 2. While |D| < M do : convert the most probable word/leaf into interior node and grow |U| leaves from it.

Analysis of Tunstall procedure Lemma Suppose D valid and PF dictionary and $U_1U_2...$ are iid. Then $H(W_1) = E[length(W_1)]H(U_1)$. Now nbr of bits/letter $= \frac{\lceil log \mid D \rceil}{E[length(W_1)]} = \frac{\lceil log \mid D \rceil}{H(W_1)}H(U_1)$. Universal Source Coding Lemma If W is a RV taking values in D and for each $w \in D$ $qp_0 < Pr(W = w) < q$. Then

 $\lceil log|D| \rceil - log\frac{1}{p_0} \leq H(W) \leq \lceil log|D| \rceil. \ \ \, \text{Corollary}$ Given U and p_U , $\varepsilon > 0$ there exists a dictionary based code which $nbrofbits/letter \leq H(U)(1+\varepsilon)$. LempelZiv method - Data compression 0. Set D=U 1. Associate to each $w \in D$ a $\lceil log|D| \rceil$ bit binary representation based on dictionry order. 2. Parse the next word w from the source sequence using D, emit the representation of w. 3. Set $D \leftarrow (D \setminus \{w\}) \cup \{wu : u \in U\}$. 4. Go to 1. Analysis of LempelZiv Technique Compare LZ to an

adversary: adversary knows before have $u_1u_2...$ designs a FSM to compress this sequence. And show LZ does as well as the adversary.

Information-Lossless FSM Compressors A Finite-State-Machine is 1. Set S of states $|S| < \infty$. 2. Initial special state $s_0 \in S$. 3. Next state function $g: SxU \to S$. 4. $f: SxU \to \{0,1\}^*$. A legitimate machine has to verify : $\forall s \in S \forall u_1...u_m \neq v_1...v_n$ if $g(s,u_1...u_m) = g(s,v_1...v_m) \Rightarrow f(s,u_1...u_m) \neq f(s,v_1...v_n)$. IL A legitimate FSM is information-lossless.

Lower bound on the output length of an IL FSM Compressor Fact Suppose m numbers $a_1...a_m \geq 0$ with $\sum_{i=1}^m a_i = k$. Then, $\sum_{i=1}^m a_i log \frac{a_i}{8m} \geq klog \frac{k}{8m}$ (with eq. for $a_i = \frac{k}{m}$).

Optimality of LempelZiv TODO

_ Channels

Communication Channels Def $P_{e,i} = Pr(U_i \neq V_i)$. $\bar{P}_e = \frac{1}{L} \sum_{i=1}^{L} Pr(U_i \neq V_i)$

Discrete Memoryless Channels A channel is said to be *memoryless* if

 $Pr(Y_i = y | X_i = x_i, past) = Pr(Y_i = y | X_i = x_i)$ *Encoder* function $f:1,...,M\to\mathcal{X}^n$.

Decoder function $\Phi: \mathcal{Y}^n \to \{1, ..., M\}$

Recall $h_2(\alpha) = \alpha log(\frac{1}{\alpha}) + (1-\alpha)log(\frac{1}{1-\alpha})$

Theorem "Bad news" No matter how the encoder and decoder are designed, we have

 $h_2(\bar{P_e}) + P_e log(|U|-1) \geq \tau_s(\frac{H}{\tau_s} - \frac{C}{\tau_c})$. Or if R > C we show that any design with $rate \geq R$, we can't make bot error prob closer to 0 then some $\delta(C,R)>0.$

Lemma $h_2(\frac{1}{L}\sum_{i=1}^{L} p_i) \ge \frac{1}{L}\sum_{i=1}^{L} h_2(p_i)$ Rate $rate(f) = R = \frac{k}{\pi} \equiv R = \frac{log M}{\pi}$

Probability of error

 $P_{e,i} = Pr(\Phi(Y_1...Y_n) \neq i | (X_1...X_n) = f(i)).$

Average prob. of error $P_{e,avg} = \frac{1}{M} \sum_{i=1}^{M} P_{e,i}$. Maximal prob. of error $P_{e,max} = max_{1 \leq i \leq M} P_{e,i}$. Examples of Discrete Memoryless Channels (BSC and BEC) TODO

Transmission with or without feedback TODO Channel Capacity $C = max_{P_X}I(X;Y)$ with I(X;Y) = H(X) - H(X|Y).

Theorem Given a channel P(y|x) with C = maxI(X;Y) then any R < C is achievable. Fano's Inequality Suppose U and V RVs taking values in set \mathcal{U} . Let $P_{e,i} = Pr(U_i|V_i)$, then $H(U_i|V_i) \le h_2(P_{e,i}) + P_{e,i}log(|\mathcal{U}| - 1).$

Theorem "Good news" If $\frac{H}{\tau_s} < \frac{C}{\tau_c}$ can achieve

 $\bar{P}_e \rightarrow 0$. Or if $R < C, \varepsilon > 0$ then there exists an Enc/Dec s.t. $rate \geq R, P_{e,max} < \varepsilon$

Converse to the Channel Coding Theorem TODO Proof of the Channel Coding Theorem TODO Capacity of BSC and BEC Binary Symmetric Channel $\mathcal{X} = \mathcal{Y} = \{0, 1\}.$

 $p(y|x) = \{ \begin{array}{ll} 1 - \delta & , x = y \\ \delta & , else \end{array} | I(X;Y) =$

 $H(Y) - H(Y|X) = H(Y) - h_2(\delta) \le 1 - h_2(\delta)$. If we choose $p_X = (\frac{1}{2}, \frac{1}{2})$ then $p_Y = (\frac{1}{2}, \frac{1}{2})$. So $C=1-h_2(\delta)$ bits.

Binary Erasure Channel $\mathcal{X} = \{0,1\}$ and

 $\mathcal{Y} = \{0, 1, e\}. \ p(y|x) = \{ \begin{array}{cc} 1 - \varepsilon & , x = y \\ \varepsilon & , y = e \end{array}$

 $I(X;Y) = H(X) - H(X|Y) = (1 - \varepsilon)H(X) \le 1 - \varepsilon. \quad P[X \in T^n(\varepsilon)] \xrightarrow[n \to \infty]{} 1.$ If we choose $p_X = (\frac{1}{2}, \frac{1}{2})$. So $C = 1 - \varepsilon$ bits.

___ Concavitv _

Recall convexity concavity f is convex if $\forall x_1 \in D, \forall x_2 \in D, \forall \theta \in [0,1]$ $f(\theta x_1 + (1 - \theta)x_2) < \theta f(x_1) + (1 - \theta)f(x_2).$ f is concave if $\forall x_1 \in D, \forall x_2 \in D, \forall \theta \in [0,1]$ $f(\theta x_1 + (1-\theta)x_2) > \theta f(x_1) + (1-\theta)f(x_2) \Leftrightarrow -f$ is convex.

f is linear if $\forall x_1 \in D, \forall x_2 \in D, \forall \theta \in [0,1]$ $f(\theta x_1 + (1 - \theta)x_2) = \theta f(x_1) + (1 - \theta)f(x_2).$ Properties 1. If f_1, f_2 convex and C_1, C_2 non negative then $f(x) = C_1 f_1(x) + C_2 f_2(x)$ convex. 2. Any local minimum is a global minimum, 3. Tangent line lies below function. 4. q convex and h linear $\Rightarrow q(h(x))$ convex.

Jensen's Inequality Theorem If f is convex and Xanx RV on D then $f(E[X]) \leq E[f(X)]$. (idem concavity >).

Concavity of Mutual Information in Input Distribution Theorem Fix p(y|x), $I(p_X) = I(X;Y)$ is concave.

KKT Conditions *Def* $(P_1,...,P_k)$ satisfies KKT if $\exists \lambda$ s.t. $\forall i, \frac{\partial f}{\partial p_i} = \lambda$ for $p_i > 0$ and $\frac{\partial f}{\partial p_i} \leq \lambda$ for $p_i = 0$.

Theorem For concave differentiable $f(P_i)$,

 $(P_1,...,P_k) \in argmax_{\sum P_i=1,P_i>0} f(P_1,...,P_k)$ iif it satisfies the KKT conditions.

KKT Conditions (cont'd) Theorem $p(x) \in argmaxI(X;Y)$ iif $\exists \lambda$ s.t.

 $\forall x \sum_{y} p(y|x) log(\frac{p(y|x)}{p(y)}) \leq \lambda$. With eq. for

p(x) > 0, if so then $C = \lambda$.

Application of KKT: Capacity of Z Channel Capacity

 $C = \log(1 + 2^{-\frac{h_2(\delta)}{1 - \delta}}) = \lambda$ $p_x^*(0) = 1 - \frac{1}{(1 - \delta)(1 + 2^{-\frac{h_2(\delta)}{1 - \delta}})}$

Continuous Alphabet: Differential Entropy

 $h(X) = E[-log f_X(X)] = -\int f_X(x)log(f_X(x))dx.$ $h(Y|X) = -E[log f_{X|Y}(X|Y)].$

 $h(X,Y) = E[-log f_{XY}(X,Y)].$

 $D(f||g) = E_f[log\frac{f_X(X)}{g_X(X)}] = \int f_X(x)log\frac{f_X(x)}{g_X(x)}dx.$

 $D(f_{XY}||f_Xf_Y) = \int \int f_{XY}(x,y) \log \frac{f_{Y|X}(y|x)}{f_Y(y)} dxdy$ Properties of differential entropy

1. I(X;Y) = h(X) - h(X|Y) = h(Y) - h(Y|X).

2. D(f||q) > 0 with eq for f = q.

3. I(X;Y) > 0 with eq for X and Y indepdt.

4. Conditioning reduces h: h(X|Y) < h(X) with eq for X and Y indepdt.

5. Chain Rule : $h(X_1, ..., X_n) =$

 $h(X_1) + h(X_2|X_1) + ... + h(X_n|X_1...X_{n-1}).$

6. $h(X_1, ..., X_n) \leq \sum_{i=1}^n h(X_i)$.

Entropy-typical sequences Discrete $|T^n(\varepsilon)| = 2^{n(H(X) + \delta(\varepsilon))}$. Continuous

 $Vol(T^n(\varepsilon)) = 2^{n(h(X) + \delta(\varepsilon))}$.

 $\begin{array}{l} \textit{Theorem } \lim_{\Delta \to 0} (H(X_\Delta) + log \; \Delta) = h(X). \\ \textit{Quantization Theorem } I(X_\Delta); Y_\Delta) \xrightarrow[\Delta \to 0]{} I(X;Y) \end{array}$

 $\mathcal{X} \sim N(0,\sigma^2)$ and $f_X(x) = rac{1}{\sqrt{2\pi\sigma^2}} e^{-rac{x^2}{2\sigma^2}}.$ Then $h(X) = E[-log_e f_X(X)] = \frac{1}{2}log_e(2\pi e\sigma^2)Nats =$ $\frac{1}{2}log_2(2\pi e\sigma^2)Bits$. Theorem "Maximal entropy" If $Var[X] = \sigma^2$, then $h(X) < \frac{1}{2}log(2\pi e\sigma^2)$ with eq for $X \sim N(\mu, \sigma^2)$ for some μ . Capacity under cost constraint

 $C(P) = \max_{f_X: E_f[b(X)] < P} I(X;Y)$

Capacity of AWGN: Additive White Gaussian Noise Y = X + Z, $Z \sim N(0, \sigma^2)$. $C(P) = \frac{1}{2}log(1 + \frac{P}{2})$ Converse to the channel coding theorem with cost constraint Theorem If $\frac{1}{\tau_s} > \frac{C(P)}{\tau_c}$, (any code with $\sum_{=u} [p(u) \frac{1}{n} \sum_{i=1}^n b(x_i^u \leq P))$ has a bit error rate $\bar{P}_e \rightarrow 0$ which can't be arbitrarily small.

Lemma $\sum_{i=1}^{n} I(X_i; Y_i) \leq nC(P)$. Parallel Gaussian channels (water-filling) With KKT $\exists \lambda \dots$ so $P_i = max\{0, \lambda - \sigma_i^2\}$. Choose λ so that $\sum_{i=1}^{k} P_i = P$. Indeed, λ : water-level and shaded areas : P_i .

Proof of Channel Coding Theorem for general channels via Threshold Decoding Theorem $\forall R < C(P), \forall \varepsilon > 0, \exists n \exists code \text{ with }$

 $\forall m, \frac{1}{n} \sum_{i=1}^{n} b(X_i^{(n)}) \leq P \text{ and } P_{max} \leq \varepsilon.$ $P_{max} = max_m P[error|m]$

 $P_{avg} = \frac{1}{M} \sum_{m_1}^{M} P[error|m].$

Corollary If $\frac{H}{\tau_s} < \frac{C(P)}{\tau_c}$ can achieve $\bar{P_e} \to 0$. Distances _

Channel Codes Code for BSC: $M = 2^{nR}$. Given the code we see (n, nR) as visible parameters. Minimum Distance Hamming distance

 $d_H(\bar{x},\bar{y}) = \#\{i: y_i \neq x_i\}$ so maximum-likehood \equiv minimum distance. minimum distance of C to these parameters $d = d_H(C) = min_{x,x' \in C, x \neq x'} d_H(x,x')$. Hamming ball with center \bar{x} and radius r

 $B(\bar{x},r) = \{\bar{y} \in \{0,1\}^n : d_H(\bar{y},\bar{x}) < r\}.$ Also note $|B(\bar{x},r)| = 1 + \binom{n}{1} + \dots + \binom{n}{n}$

Theorem Given $\bar{x}, \bar{y}, \bar{z} \in \{0,1\}^n$. $d_H(\bar{x}, \bar{y}) \geq 0$ with eq if $\bar{x} = \bar{y}$. $d_H(\bar{x}, \bar{y}) = d_H(\bar{y}, \bar{x})$.

 $d_H(\bar{x},\bar{z}) \le d_H(\bar{x},\bar{y}) + d_H(\bar{y},\bar{z}).$

Corollary Suppose $\bar{x}, \bar{x'} \in \{0,1\}^n$ with

 $d=d_H(\bar{x},\bar{x'})$. Set $r=\lfloor \frac{d-1}{2} \rfloor$. Consider $B(\bar{x},r)$ and $B(\bar{x'},r)$ then they are disjoint.

Singleton Bound (Bad news) If

 $\#ofcodewords = M > 2^k \text{ then } d_{min} \leq n - k.$ Sphere-packing Bound (Bad news) Suppose

 $C \subset \{0,1\}^n$ is a binary code with M codewords and

 $d=d_{min}.$ Then, $M\left[\sum_{i=0}^{r=\lfloor \frac{d-1}{2} \rfloor} \binom{n}{i}
ight] \leq 2^n.$

GilbertVarshamov Bound (Good news) For every (n,M,d) satisfy $d_{min}=d$ and $M\left[\sum_{i=0}^{d-1}\binom{n}{i}\right]\geq 2^n$ there exists a code $C \subset \{0,1\}^n$ with > Mcodewords and $d_{min}(C) \geq d$.

Linear Codes A code $C \subset \{0,1\}^n$ is said to be *linear* if $x, y \in C$ then $x + y \in C \equiv C$ is a vector space in $\{0,1\}^n$.

Generator Matrix Fact 1 If C is a linear code, then $|C|=2^k$ for some int k and there exists a $k\times n$ binary matrix G s.t.

 $C = \{[u_1...u_k]G : (u_1...u_k) \in \{0,1\}^k\} \equiv C \text{ is a raw }$ space of G.

Parity-check Matrix Fact 2 If C is a linear code with $|C|=2^k$, then there exists a $n\times(n-k)$ matrix H s.t. $C = \{\bar{x} : \bar{x}H = [0...0]\}.$

Hamming Codes Fact. For the BSC, given $R < C, \varepsilon > 0$ there exists a liner code C s.t. $rate > R, p(error) < \varepsilon$. The Hamming weight

 $w_H(x)$ of a vector $x \in \{0,1\}^n$ is $w_H(x) = \sum_{i=1}^n \mathbb{1}\{x_i \neq 0\} = d_H(x, 0...0)$. Given a

linear code C, let $w_{min}(C) = min_{x \in C, x \neq 0} w_H(x)$. Theorem For a linear code C. let

 $w_{min}(C) = d_{min}(C).$

Field $(\mathbb{F}, +, .)$ is a *field*. $a, b \in \mathbb{F} \Rightarrow a + b \in \mathbb{F}, a, b \in \mathbb{F}$. Properties

a + b = b + a, a.b = b.a, (a + b) + c = a + (b + c), $(a.b).c = a.(b.c), \exists O \in \mathbb{F} \text{ s.t. } 0 + a = a, \exists 1 \in \mathbb{F} \text{ s.t.}$

 $1.a = a, \forall a \in \mathbb{F}, \exists (-a) \text{ s.t. } a + (-a) = 0,$ $\forall a \neq 0, \exists (a^{-1}) \text{ s.t. } a.(a^{-1} = 1),$

a.(b+c) = a.b + a.c. Theorem "Galois" Any finite field is isomorphic to one of $\mathbb{F} = \{$ polynomial of degree < k} with coeff. +: poly additive modp . : poly mult. modp cond $x^k = ...$ (degree $\leq k - 1$).

Corollary Finite field exist only with $|\mathbb{F}| = p^k$ (prime power). Linear codes (general F) $C \subset \mathbb{F}^k$ is linear if $\forall x, x' \in C, \forall a, a' \in \mathbb{F}, a.x + a'.x' \in C.$

Reed-Solomon Codes Given a field $\mathbb{F}, n < |\mathbb{F}|, k < n$. Construct a linear code C with $C \subset \mathbb{F}^n$ and $|C| = |\mathbb{F}|$ as follows: Pick $\alpha_1 \in \mathbb{F}$, $\alpha_2 \in \mathbb{F}$, ...

 $\alpha_n \in \mathbb{F}$ s.t. $\alpha_i \neq \alpha_i$ for $i \neq j$. with $u(D) = u_0 + u_1 D + \dots + u_{k-1} D^{k-1}$

 $C = \{(u(\alpha_1), ..., u(\alpha_n)) : (u_0...u_{k-1}) \in \mathbb{F}^k\}$ called a

Reed - Salomon code. Obs. If C is a RS code, then C is linear and $d_{min}(C) = w_{min}(C)$. Theorem An (n,k) RS code has $d_{min}=n-(k-1)$. Any code

 $C\subset \mathbb{F}^k$ with $|C|>|\mathbb{F}|^{k-1}$ has

 $d_{min}(C) \leq n - (k-1).$

Polar Codes Perfect channel p(y|0).p(y|1) = 0, C=1, trivial code : $m=0 \rightarrow 0$ or $1 \rightarrow 1$. Useless channel p(y|0) = p(y|1) i.e. Y indpt of X, C = 0, trivial code : $m=0 \rightarrow X=0$ is optimal. Mediocre channel If we can convert a mediocre channel into a

mixture of the "perfect" and "useless" channels, then communication can take place by means a trivial codes. Conversion method

 $2I(p) = I(p^{-}) + I(p^{+}), I(p^{-}) \le I(p) \le I(p^{+})$

Maths .

Disjoint $P(E_1 \cup E_2) = P(E_1) + P(E_2)$



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