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§1. Entropy, Divergence, and Mutual Information
 1
            H(X) := -\sum_{x} p_X(x) \log p_X(x) = -\mathbb{E}(\log p_X(x)) D(p||q) := \sum_{x} p(x) \frac{p(x)}{q(x)} = \mathbb{E}(\log \frac{1}{q(X)}) - H(X)
 2
            I(X;Y) := \sum_{x,y} p_{X,Y}(x,y) \log \frac{p_{X,Y}(x,y)}{p_X(x)p_y(y)} = D(p_{X,Y}||p_Xp_Y) = H(X) + H(Y) - H(X,Y) = H(X) - H(X,Y)
      H(X|Y) = H(Y) - H(Y|X)
            H(Y|X) = -\sum_{x,y} p_{X,Y}(x,y) \log p_{Y|X=x}(y) = -\sum_{x} p_X(x) \mathbb{E}(\log p_{Y|X=x}(Y)) = -\mathbb{E}(\log p_{Y|X}(Y)) = -\mathbb{E}(\log p_{Y|X}(Y))
      \sum_{x} H(Y|X=x) \mathbb{P}(X = x) = H(X,Y) - H(X)
            I(X;Y|Z) := H(X|Z) - H(X|Y,Z)
            Gibb's Inequality H(X) = -\sum_x p(x) \log p(x) \le -\sum_x p(x) \log q(x) (= iff p = q)
            D(p_{X,Y}||p_{\hat{X},\hat{Y}}) = D(p_{Y|X}||p_{\hat{Y}|\hat{X}}||p_{X}) + D(p_{X}||p_{\hat{X}})
10
            D(p_{Y|X}||p_{\hat{X},\hat{Y}}|p_X) = D(p_X p_{Y|X}||p_X p_{\hat{Y}|\hat{X}})
            D(p_{Y|X}||q_{Y|X}|p_X) = \sum_x p_X(x)D(p_{Y_1|X=x}||q_{Y_2|X=x})
12
            Logsum: a_i, b_i \ge 0 \Longrightarrow \sum_{i=1}^n a_i \log \left(\frac{a_i}{b_i}\right) \ge \left(\sum_{i=1}^n \log \left(\frac{\sum_{i=1}^n a_i}{\sum_{i=1}^n b_i}\right)\right) \text{ Pf) } q_i = a_i / \sum_{i=1}^n a_i \text{ and Gibbs}
13
            D(\lambda p_1 + (1 - \lambda)p_2||\lambda q_1 + (1 - \lambda)q_2) \le \lambda D(p_1||q_1) + (1 - \lambda)D(p_2||q_2) for \lambda \in [0, 1] (Pf: logsum)
14
                                                                      I(X;Y) = H(X) - H(X|Y)
            I(X;Y) \ge 0 (= iff X \perp Y)
15
                                                                             I(X_1, \dots, X_n; Y) = \sum_{i=1}^{n} I(X_i; Y | X_{i-1}, \dots, X_1) (Chain)
            H(X,Y) = H(X) + H(Y|X)
16
            Data Processing (X \perp Z)|Y \Longrightarrow I(X;Y) \ge I(X;Z) Pf) Chain I(Y,Z;X) and I(Z,Y;X)
17
            f: \mathcal{X} \to \mathcal{Y} \Longrightarrow I(X; Y) \ge I(X; f(Y))
18
19
            0 \le H(X) \le \log(|\mathcal{X}|)
                                                        (= iff X const, X uniform respectively)
20
            0 \le H(X|Y) \le H(X)
                                                          (2^{\operatorname{nd}} = \operatorname{iff} X \perp Y \operatorname{iff} X = f(Y))
21
            \begin{array}{l} H(f(X)) \leq H(X) \quad \text{ (= iff $f$ bijective)} \\ H(X_1, \cdots, X_n) = \sum_{i=1}^n H(X_i|X_{i-1}, \cdots, X_1) \leq \sum_{i=1}^n H(X_i) \quad \text{ (= iff $X_i$ indep)} \\ X, Y \text{ iid} \Longrightarrow \mathbb{P}(X = Y) \geq 2^{-H(X)} \quad \text{ (= iff uniform, proof by Jensen)} \end{array}
22
23
24
            Fano's Inequality H(X|Y) \le H(\mathbf{1}_{X\neq Y}) + \mathbb{P}(X\neq Y)\log(|\mathcal{X}|-1)
                                                                                                                                            (Proof by defining Z = \mathbf{1}_{X \neq Y}
25
       and H(Z|X,Y) = 0, so that H(X|Y) = H(Z|Y) + H(X|Y,Z)
26
            Cor: H(X|Y) \le 1 + \mathbb{P}(X \ne Y) \log(|\mathcal{X}| - 1)
27
28
            Max Entropy Tip: Use Gibb's to bound H(q), and equality iff p = q where p specified as:
29
            For \mathbb{E}(X) = const. on \{1, \dots\}, X \sim \text{geom}(p) \in \{1, \dots\}, \mathbb{E}(X) = \frac{1}{p}, H(X) = \frac{-(1-p)\log 1 - p - p \log p}{p}
For \mathbb{E}(X) = const. on \{0, \dots\}, X \sim \text{geom}(p) \in \{0, \dots\}, \mathbb{E}(X) = \frac{1-p}{p}, H(X) = \frac{-(1-p)\log 1 - p - p \log p}{p}
30
31
            Max Entropy for \mathbb{E}(f(X)) = C, X \sim p_X(x) = \frac{e^{-\lambda f(x)}}{\sum_x e^{-\lambda f(x)}} where \lambda chosen s.t. \mathbb{E}(f(X)) = C
32
33
            \overline{\mathbf{\S 2. AEP WLLN: } \bar{X_n} \overset{P}{\to} \mu} \text{ (ie: } \lim_{n \to \infty} \mathbb{P} \left( |\bar{X_n} - \mu| < \epsilon \right) = 1 \text{ for any } \epsilon > 0 \right)}
            Weak AEP 1: -\frac{1}{n}\log p_{X_1,\dots,X_n}(X_1,\dots,X_n) \xrightarrow{P} H(X)
\mathcal{T}_n^{\epsilon} \coloneqq \left\{ (x_1,\dots,x_n) \in \mathcal{X}^n : \left| -\frac{1}{n}\log p_{X_1,\dots,X_n}(x_1,\dots,x_n) - H(X) \right| \le \epsilon \right\}
35
36
            \forall \epsilon > 0, \exists N \text{ s.t. } \forall n \geq N,
37
            (i) p_{X_1,\dots,X_n}(x_1,\dots,x_n) \in [2^{-n(H(X)+\epsilon)}, 2^{-n(H(X)-\epsilon)}] for any (x_1,\dots,x_n) \in \mathcal{T}_n^{\epsilon}
38
      (ii) \mathbb{P}((X_1, \dots, X_n) \in \mathcal{T}_n^{\epsilon}) \ge 1 - \epsilon (From weak AEP 1)

(iii) |\mathcal{T}_n^{\epsilon}| \in [(1 - \epsilon)2^{n(H(X) - \epsilon}, 2^{n(H(X)) + \epsilon}] Pf) 1 = \sum_x p_{\mathbf{X}}(\mathbf{x}) \ge \sum_{\mathcal{T}_n^{\epsilon}} p_{\mathbf{X}}\mathbf{x} \ge \sum_{\mathcal{T}_n^{\epsilon}} 2^{-n(H(X) + \epsilon)} and 1 - \epsilon \le \mathbb{P}((X_1, \dots, X_n) \in \mathcal{T}_n^{\epsilon}) \le \sum_{\mathcal{T}_n^{\epsilon}} 2^{-n(H(X) - \epsilon)} = 2^{-n(H(X) - \epsilon)} |\mathcal{T}_n^{\epsilon}|
39
41
            Shannon's 1st Thrm: \forall \epsilon > 0, \exists n \in \mathbb{Z} \text{ and } c : \mathcal{X}^* \to \{0,1\}^* \text{ s.t. } \cup_{k \geq 0} \mathcal{X}^{nk} \to \{0,1\}^*, (x_1, \cdots, x_k) \to \{0,1\}^*
42
      c(x_1)\cdots c(x_k)\in\{0,1\}^* injective and \frac{1}{n}\mathbb{E}\left(\left|c\left(X_1,\cdots,X_n\right)\right|\right)\leq H(X)+\epsilon
43
44
            §3. Optimal Codes
45
             \lceil A \rceil - 1 < A \leq \lceil A \rceil
                                                            A \leq \lceil A \rceil < A + 1
46
            Kraft-McMillan: (i) c: \mathcal{X} \to \mathcal{Y}^* uniquely decodable and l_x := |c(x)| \to \sum_{x \in \mathcal{X}} |\mathcal{Y}|^{-l_x} \le 1
47
            Pf) (\sum_{x} d^{-|c(x)|})^n = \sum_{k=nl_{\min}}^{nl_{\max}} a(k)d^{-k}, a(k) < d^k by uniq decod. Take n^{\text{th}} root and n \to \infty.
48
            (ii) Given (l_x)_{x \in \mathcal{X}} \subset \mathbb{N} and \sum_{x \in \mathcal{X}} |\mathcal{Y}|^{-l_x} \leq 1, then \exists prefix code c : \mathcal{X} \to \mathcal{Y}^* s.t. |c(x)| = l_x
49
            Pf) Relabel \mathcal{X} = \{1, \dots, |\mathcal{X}|\}, l_1 \leq \dots \leq l_{|\mathcal{X}|}. r_m := \sum_{i=1}^{m-1} |\mathcal{Y}|^{-l_i}. c(m): first m digits of r_m
50
            X be RV in finite \mathcal{X} and c (uniq decod., d-ary), then H_d(X) \leq \mathbb{E}(|c(X)|) (= iff |c(x)| = -\log_x p_X(x),
51
      Lower bd on length) Pf) Let l_x = c(x), q(x) = \frac{d^{-l_x}}{\sum_{x \in \mathcal{X}} d^{-l_x}}, consider \mathbb{E}(|c(X)|) - H_d(X)
52
            Existence of Optimal Code H_d(X) \leq \mathbb{E}(|c^*(X)|) < H_d(X) + 1 Pf) l_x = \lceil -\log_d(p(x)) \rceil Kraft-
53
      McMillan
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Shannon's Code (i) Order p_1 \geq \cdots \geq p_m. (ii) c(x_r) = \text{first } l_r := \lceil -\log_{|\mathcal{Y}|}(p_r) \rceil digits of \sum_{i=1}^{r-1} p_i
 1
           Shannon with distrib. estimation p, q (estimation) pmf on \mathcal{X},
 2
           H_d(X) + D_d(p||q) \le \mathbb{E}(|c_q(X)|) < H_d(X) + D_d(p||q) + 1
           Pf: Bound \mathbb{E}(|c_q(X)|) = \sum_x p(x) \lceil -\log_d(q(x)) \rceil

Elias' code First \lceil -\log_d(p_i) \rceil + 1 digits of \sum_{i < r} p_i + \frac{p_r}{2} \Longrightarrow H_d(X) + 1 \le \mathbb{E}(|c_E(X)|) \le H_d(X) + 2
           Bijection between d-ary prefix codes and d-ary rooted trees.
           Huffman code is optimal Pf) if p_1 \geq \cdots \geq p_m, (i) p_j > p_k \Longrightarrow |c(x_j)| \leq |c(x_k)|, (ii) two longest
      codewords have same len (iii) two longest codewords only differ in last digit. p,p'\Longrightarrow L(c^p)-L(c^{p'})=
 9
     p_{m-1} + p_m Also for e^p, e^{p'}, L(e^p) - L(e^{p'}) = p_{m-1} + p_m. Subtract each other, L(e^p) = L(e^p)
11
           §4 Channel Coding DMC (\mathcal{X}, M, \mathcal{Y}) where \mathcal{X} (input alphabet), \mathcal{Y} (output alphabet), M(|\mathcal{X}| \times |\mathcal{Y}|)
12
      stochastic matrix).
13
           Channel Capacity: C := \sup I(x; y) = H(Y) - H(Y|X)
14
           Tip: H(Y|X) = \sum_{x} H(Y|X = x) p_X(x), Use I(X,Y) = H(Y) - H(Y|X)
15
           (m,n)-channel code for DMC (\mathcal{X},M,\mathcal{Y}): tuple (c,d) where c:\{1,\cdots,m\}\to\mathcal{X}^n (Encoder) and
16
     d: \mathcal{Y}^n \to \{1, \cdots, m\} (Decoder)
17
           Rate of (m, n)-code (c, d): \rho(c, d) := \frac{1}{n} \log_{|\mathcal{X}|}(m)
18
           \overline{\epsilon_i} = \mathbb{P}\left(d(\mathbf{Y} \neq i | c(i) = \mathbf{X}) \text{ for } i = 1, \cdots, m, \ \epsilon_{\max} \coloneqq \max_{i \in \{1, \cdots, m\}} \epsilon_i, \ \overline{\epsilon} \coloneqq \frac{1}{m} \sum_{i=1}^m \epsilon_i
Rate R achievable if \forall \epsilon > 0, \ \exists suff. large. m, n and (m, n)-channel code (c, d) with \rho(c, d) > R - \epsilon
19
20
      and \epsilon_{\rm max} < \epsilon
21
           <u>Shannon's 2<sup>nd</sup> theorem</u> DMC (\mathcal{X}, M, \mathcal{Y}) with capacity C, then R > 0 achievable iff R \leq C
22
           Pf)
23
24
           \left\{(x,y) \in \mathcal{X}^n \times \mathcal{Y}^n : \max\left(\left|\frac{-\log p_{\mathbf{X},\mathbf{Y}}(x,y)}{n} - H(X,Y)\right|, \left|\frac{-\log(p_{\mathbf{X}}(x))}{n} - H(X)\right|, \left|\frac{-\log(p_{\mathbf{Y}}(y))}{n} - H(Y)\right|\right)\right\}
25
           \underline{\text{Joint AEP}}: \mathbf{X} = (X_1, \cdots, X_n), \mathbf{Y} = (Y_1, \cdots, Y_n)
26
           (i) \lim_{n\to\infty} \mathbb{P}\left( (\mathbf{X}, \mathbf{Y}) \in \mathcal{J}_{\epsilon}^{(n)} \right) = 1 (ii) |\mathcal{J}_{\epsilon}^{(n)}| \le 2^{n(H(X,Y)+\epsilon)}
27
           (iii) \exists n_0 \text{ s.t. } \forall n \geq n_0, (1-\epsilon)2^{-n(I(X;Y)+3\epsilon)} \leq \mathbb{P}\left((\mathbf{X}',\mathbf{Y}') \in \mathcal{J}_{\epsilon}^{(n)}\right) \leq 2^{-n(I(X;Y)-3\epsilon)}
28
29
           Channel Coding w/ non-iid Input
30
           Stationary stochastic process: \mathbb{P}(X_1 = x_1, \dots, X_n = x_n) = \mathbb{P}(X_{1+j} = x_1, \dots, X_{n+j} = x_n) for all
31
32
           Entropy rate of stochastic process: \mathcal{H}(X) = \lim_{n \to \infty} \frac{1}{n} H(X_1, \dots, X_n)
33
           \overline{\text{Lemma (1): Stationary Stochastic process } X, n \xrightarrow{n} H(X_n|X_{n-1},\cdots,X_1) \text{ is non-increasing and}
34
     \lim_{n\to\infty} H(X_n|X_{n-1},\cdots,X_1) exists.
35
           Lemma (2): \lim_{n\to\infty} a_n = a \Longrightarrow \frac{1}{n} \sum_{i=1}^n a_i = a
36
           Thrm: Stationary stoch. process X \Longrightarrow \mathcal{H}(X) = \lim_{n \to \infty} H(X_n | X_{n-1}, \cdots, X_1) PF) Lemma (i),(ii)
37
           Lemma (3): H(Y_n|Y_{n-1},\dots,Y_1)
38
           Lemma (4): H(Y_n|Y_{n-1},\dots,Y_2,Y_1) \leq \lim_k H(Y_{n+k+1}|Y_{n+k},\dots,Y_1) = \mathcal{H}(Y)
39
           Thrm: X(X_i)_{i\geq 1} stationary Markov. \phi: \mathcal{X} \to \mathcal{Y}, Y_i := \phi(X_i), \text{ then } H(Y_n|Y_{n-1},\cdots,Y_1,X_1) \leq
40
      \mathcal{H}(Y) \le H(Y_n | Y_{n-1}, \cdots, Y_1), \ \mathcal{H}(Y) = \lim_{n \to \infty} H(Y_n | Y_{n-1}, \cdots, Y_1, X_1) = \lim_{n \to \infty} H(Y_n | Y_{n-1}, \cdots, Y_1)
41
           PF) Lemma (3),(4)
42
43
           §Appendix
44
           Markov Inequality: \mathbb{P}(X \ge x) \le \frac{\mathbb{E}(X)}{x} for all x > 0
45
           Chebyshev Inequality: \mathbb{P}(|X - \mu| > \epsilon) \leq \frac{\sigma^2}{\epsilon^2}
46
           Optimal \neq Huffman: 0.3 = 00, 0.3 = 10, 0.2 = 01, 0.2 = 11
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