

Arithmetic Coding Summary from L7

"Language model": often given by conditional probability distributions:

$$P(x_n | \underbrace{x_1, \dots, x_{n-1}}_{x^{n-1}}) \text{ for } n=1, 2, \dots, N$$

w/ joint distribution

$$P(x^n) = P(x_1) P(x_2 | x_1) P(x_3 | x_1, x_2) \dots P(x_n | x^{n-1})$$

equivalent

↳ see last lecture notes + exercise class

Arithmetic coding:

Input: $x^N \in \mathcal{A}^N$ to compress

Algo:

* $q \leftarrow 0, r \leftarrow 1, p \leftarrow 1$

* For $n=1, 2, \dots, N$:

① $r \leftarrow q + p R(x_n | x_1, \dots, x_{n-1})$
 $q \leftarrow q + p Q(x_n | x_1, \dots, x_{n-1})$

$\sum_{y \leq x_n} P(y | x_1, \dots, x_{n-1})$
upper cumulative prob

② Write $r \leq \frac{1}{2}$ or $q \geq \frac{1}{2}$:

$$b \leftarrow \begin{cases} 0 & \text{if } r \leq \frac{1}{2} \\ 1 & \text{if } q \geq \frac{1}{2} \end{cases}$$

Write b

$$r \leftarrow 2r - b$$

$$q \leftarrow 2q - b$$

lower cumulative prob
 $\sum_{y < x_n} P(y | x_1, \dots, x_{n-1})$

③ $p \leftarrow r - q$

* Write $\lceil \log \frac{2}{p} \rceil$ bits of binary expansion of $\frac{q+r}{2}$

Average rate: $\approx \frac{H(X^N)}{N}$ for large N

Joint Entropies (§8)

Joint distribution $P(x,y) \rightarrow H(X,Y)$

* marginal distributions: $P(x), P(y) \rightarrow H(X), H(Y)$

$\hookrightarrow H(X) + H(Y) \geq H(X,Y)$, = iff X, Y independent

HW 3

* Conditional distributions: $P(y|x), P(x|y)$

$\hookrightarrow H(Y|X=x) = \sum_y P(y|x) \cdot \log \frac{1}{P(y|x)}$ & similarly $H(X|Y=y)$

Conditional entropy:

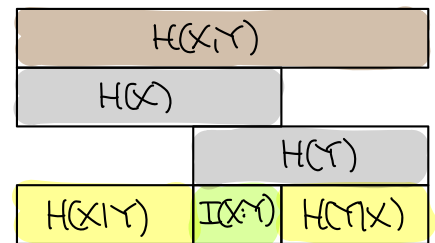
$$H(Y|X) := \sum_x P(x) H(Y|X=x)$$

* $H(Y|X) \geq 0$, = 0 iff $Y=f(X)$ for some function f

Pf: = 0 iff $H(Y|X=x) = 0 \forall x$ iff $\forall x \exists y: P(y|x) = 1$ □

* $H(Y|X) = H(X,Y) - H(X)$

Pf: $H(Y|X) = \sum_{x,y} P(x) P(y|x) \log \frac{1}{P(y|x)}$
 $= \sum_{x,y} P(x,y) \log \frac{P(x)}{P(x,y)} = H(X,Y) - H(X)$. □

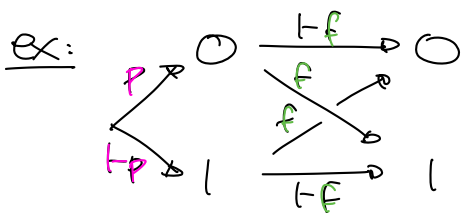


* $H(Y|X) \leq H(Y)$, = iff X, Y independent ⊗

Pf: eqv to $H(X,Y) \leq H(X) + H(Y) \forall$ □

* Chain rule: $H(Y,Z|X) = H(Y|X) + H(Z|X,Y)$

Pf: RHS = $H(Y|X) - H(X) + H(X,Y,Z) - H(X,Y) =$ LHS. □



$$H(Y|X) = p \cdot H(\{1-f, f\}) + (1-p) \cdot H(\{f, 1-f\})$$

$$\Rightarrow H(\{f, 1-f\}) = \begin{cases} 0 & \text{if } f=0 \text{ OR } f=1 \\ 1 & \text{if } f=\frac{1}{2} \end{cases}$$

independent of p !

ex: $N = \#$ coin flips of biased coin until 1st heads
 $H(N) = ?$ Trick: $X = \begin{cases} 1 & \text{if 1st outcome is heads } (N=1) \\ 0 & \text{otherwise } (N>1) \end{cases}$



$1-p$ $T < \dots$

$$\begin{aligned} \Rightarrow H(N) &\stackrel{X=f(N)}{=} H(N, X) = H(X) + H(N|X) \\ &= H(X) + p \cdot H(N|X=1) + (1-p) \cdot H(N|X=0) \\ &= H(\{p, 1-p\}) \quad \quad \quad \begin{matrix} = 0 \text{ since } N=1 \\ \text{if } X=1 \end{matrix} \quad \quad \quad \underbrace{H(N|X=0)}_{= H(N)} \end{aligned}$$

$$\Rightarrow H(N) = \frac{H(\{p, 1-p\})}{p}$$

Mutual information:

$$I(X:Y) = H(X) + H(Y) - H(X,Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

- * $I(X:Y) \geq 0$, = 0 iff X, Y independent
 - * $I(X:Y) \leq H(X), H(Y)$
- } reformulations of facts for $H(Y|X), H(X|Y)$ from above

* $I(X:Y) = D(P_{XY} || Q_{XY})$, where $Q(x,y) = P(x)P(y)$

EX CLASS

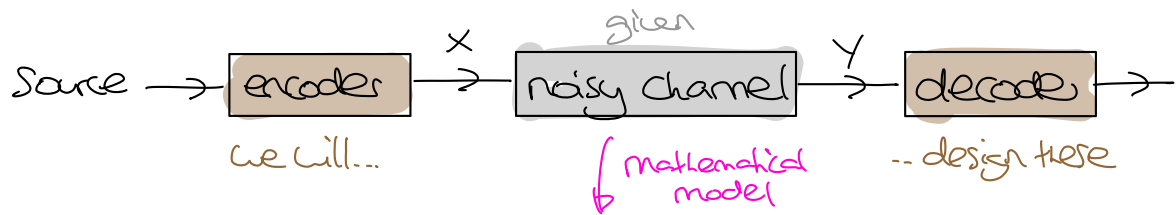
Recall: Relative entropy: $\frac{p}{q}$ etc!?! let's discuss!

$$D(P||Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)} \in [0, \infty]$$

* $D(P||Q) < \infty \iff \forall x: Q(x) = 0 \Rightarrow P(x) = 0$

* Gibbs inequality: $D(P||Q) \geq 0$, = 0 iff $P=Q$

Communicating over noisy channels (§9)

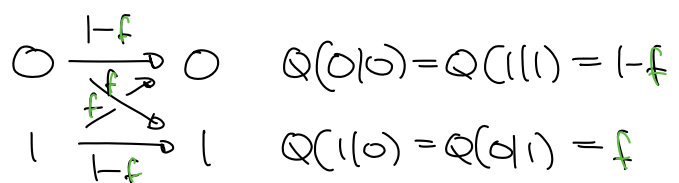


(Discrete memoryless) channel: $Q(y|x)$ cond. probability dist.

where $x \in \mathcal{X}$ input alphabet, $y \in \mathcal{Y}$ output alphabet

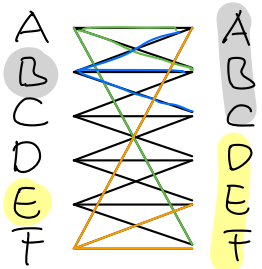
eg. ① Binary symmetric channel:

(our old friend)



② Binary asymmetric channel: $0 \xrightarrow{f} 0$ $Q(0|0)=1, Q(1|0)=0$
 $1 \xrightarrow{1-f} 1$ $Q(0|1)=f, Q(1|1)=1-f$
 (from HW1)

③ Binary erasure channel: $0 \xrightarrow{1-f} 0$ $Q(\perp|0)=Q(\perp|1)=f$
 $ \searrow^f \perp$ $Q(0|0)=Q(1|1)=1-f$
 $1 \xrightarrow{1-f} 1$ $Q(1|0)=Q(0|1)=0$
 $ \searrow^f \perp$
 $\mathcal{X} = \{0, 1\}$ $\mathcal{Y} = \{0, 1, \perp\}$

④ Noisy typewriter:  $Q(A|A)=Q(B|A)=Q(F|A)=\frac{1}{3}$
 $Q(B|0)=Q(C|B)=Q(A|B)=\frac{1}{3}$
 \vdots
 $Q(F|F)=Q(A|F)=Q(E|F)=\frac{1}{3}$

How well can we communicate over each of them?

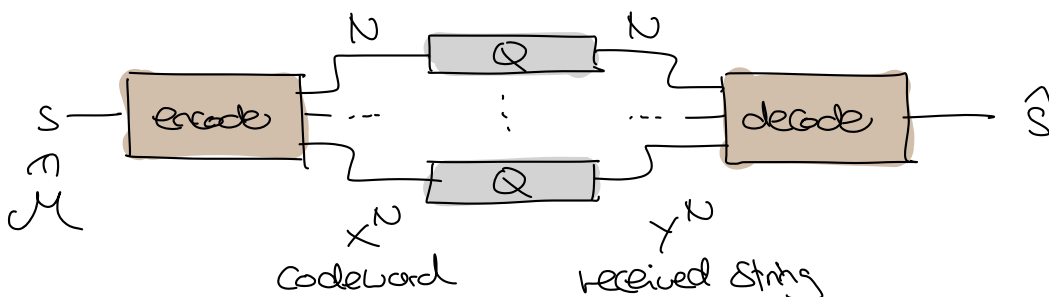
- * If we allow no errors at all: ① \downarrow any y could come from either x
 - ② \downarrow $y=0$ can come from any x (sending 0 all the time is not informative)
 - ③ \downarrow $y=1$ can come from either x
 - ④ \Rightarrow encode $0 \mapsto B$ decode $A, B, C \mapsto 0$
 $1 \mapsto E$ decode $D, E, F \mapsto 1$
- "zero error comm."
 EX CLASS

* If we allow error: Can use Bayes' theorem to infer most likely x :

$$P(x|y) = \frac{Q(y|x)P(x)}{\sum_z Q(y|z)P(z)}$$

← assuming x come from some ensemble
 ↳ Lecture 1 & 2

For reliable communication, consider block encodings:



WANT: $S = \hat{S}$
 with high probability
 e.g. for S uniform

Rate $R = \frac{\log \#M}{N}$ bits per channel use

e.g. $R = \frac{\log \#M}{N}$ for N-fold repetition code

the larger the better

Capacity of a channel $Q(y|x)$ is defined as:

$$C(Q) = \max_{P(x)} I(X:Y)$$

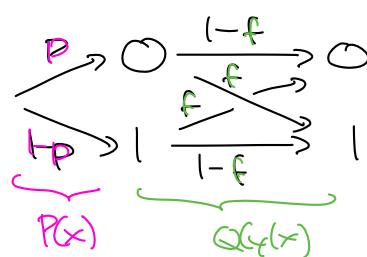
for $P(x, Y) = P(x) \cdot Q(y|x)$

Next week we will discuss **Shannon's Noisy Coding Theorem**, which states that $C(Q)$ is the "optimal" rate at which we can communicate "reliably" via the channel $Q(y|x)$.

e.g. for the binary symmetric channel:

$$\begin{aligned} * I(X:Y) &= H(Y) - H(Y|X) \\ &= H(Y) - \underbrace{H(\{f, 1-f\})}_{\text{indep of } p} \end{aligned}$$

|| see above ▽



$$* \max_p H(Y) = 1 \quad \text{since } P(Y=0) = p(1-f) + (1-p)f = \frac{1}{2} \text{ if } p = \frac{1}{2}$$

$$\Rightarrow C(Q) = \max_p I(X:Y) = 1 - H(\{f, 1-f\}) = \begin{cases} 0 & \text{if } f = \frac{1}{2} \\ 1 & \text{if } f = 0 \text{ or } f = 1 \\ \text{in between otherwise} \end{cases}$$

Intuitive ▽