

Wrapping up the Probability Recap

Recall: For a "numerical" random variable X , we defined

* **expectation value** or **mean**: $EX = E[X] = \sum_x P(x) \cdot x$

* **variance**: $Var(X) = E[(X - EX)^2]$
 $\stackrel{\text{ex}}{=} E[X^2] - (EX)^2$

Examples

P	Bernoulli (f)	Binomial (n, f)
E	f	$\xrightarrow{\text{ex}} n \cdot f$
Var	f(1-f)	n \cdot f \cdot (1-f)

$$E[(X - EX)^2] = E[(X - f)^2]$$

$$= f(1-f)^2 + (1-f)(0-f)^2 = f(1-f)$$

Three results that give these meaning:

Markov inequality: If $X \geq 0$: $Pr(X \geq t) \leq \frac{E[X]}{t} \quad (\forall t > 0)$

PF: $Pr(X \geq t) = \sum_{x \geq t} P(x) \leq \sum_{x \geq t} P(x) \frac{x}{t} \leq \frac{E[X]}{t} \quad \square$

Chebyshev inequality: $Pr(|X - EX| \geq \epsilon) \leq \frac{Var(X)}{\epsilon^2}$

With high probability (WHP) deviation from mean is of order $\sqrt{Var(X)}$

PF: Apply Markov to $Y = (X - EX)^2$. □

Law of large numbers: Suppose $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P$ with $\begin{cases} \text{mean } \mu \\ \text{variance } \sigma^2 \end{cases}$.
 Let $\bar{X} := \frac{1}{n} (X_1 + \dots + X_n)$. Then:

$$Pr(|\bar{X} - \mu| \geq \epsilon) \leq \frac{1}{n} \frac{\sigma^2}{\epsilon^2}$$

WHP: empirical average \approx expectation value

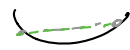
PF: $E\bar{X} = \mu$ & $Var(\bar{X}) = \frac{1}{n^2} Var(X_1 + \dots + X_n) = \frac{\sigma^2}{n}$. \rightarrow Chebyshev. □

Convex and concave functions (§2.7)

Suppose $f: I \rightarrow \mathbb{R}$ is function on interval $I = (a, b)$

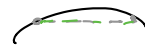
$a = -\infty$ or $b = \infty$
allowed

We say f is **Convex** if $f'' \geq 0$



\exp, x^2, \dots

Concave if $f'' \leq 0$



\log, \sqrt{x}, \dots

Jensen's inequality: Let Z be a RV.

If f is convex: $E[f(Z)] \geq f(EZ)$

If f is concave: $E[f(Z)] \leq f(EZ)$

i.e. $\sum_z P(z) f(z) \begin{matrix} \geq \\ \leq \end{matrix} f\left(\sum_z P(z) z\right)$

If $f'' > 0$ or $f'' < 0$: "=" holds only if Z is constant!

Entropy (§2.4)

Entropy of a random variable (RV) X with distribution P :

$$H(X) := H(P) := \sum_x P(x) \cdot \log \frac{1}{P(x)} = E\left[\log \frac{1}{P(X)}\right]$$

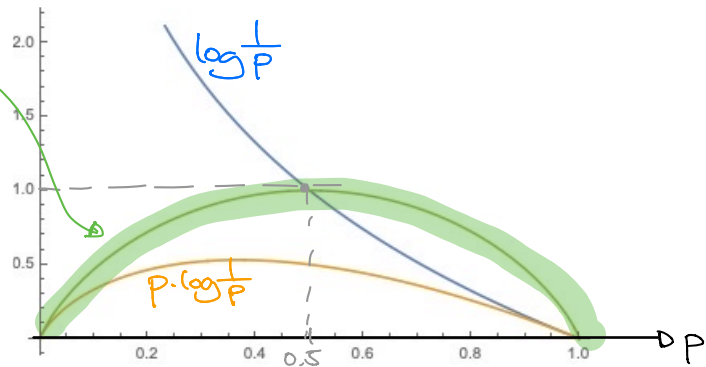
$0 \cdot \log \frac{1}{0} = 0$ always base 2

Unit "bit"

Eg. $X \sim \text{Bernoulli}(p)$: **binary entropy**

$$H(X) = p \cdot \log \frac{1}{p} + (1-p) \cdot \log \frac{1}{1-p}$$

$e \in [0, 1]$



Properties:

* $H(X) \geq 0$, = iff constant $p \cdot \log \frac{1}{p} \geq 0 \quad \forall p \in [0, 1]$, = iff $p=0$ or $p=1$

* $H(X) \leq \log \#\{x: P(x) > 0\} \leq \log \#\Omega_X$

$H(X) = \log \#\Omega_X \iff X$ uniformly random

} Pf: Apply **Jensen** with $f = \log$ and $Z = \frac{1}{P(X)}$:

$$E\left[\log \frac{1}{P(X)}\right] \leq \log E\left[\frac{1}{P(X)}\right]$$

with equality iff $P(X)$ constant, i.e. $P(x) > 0, P(y) > 0 \implies P(x) = P(y)$ \square

* NOTATION: $H(X, Y) = H(XY) =$ entropy of joint distribution $P(x, y)$

If X, Y independent: $H(X, Y) = H(X) + H(Y)$

Pf: Since $P(x, y) = P(x)P(y)$ we have $\log \frac{1}{P(x, y)} = \log \frac{1}{P(x)} + \log \frac{1}{P(y)}$
 \leadsto take expectation values. □

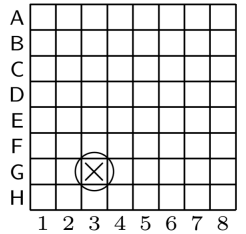
Interpretation? Let us call $h(x) = h(X=x) = \log_2 \frac{1}{P(x)}$ the **information content** (or "surprisal") of an outcome $x \in \Omega_X$.

$\Rightarrow H(X) = E[h(X)]$ is average information content.

Why is this a good definition? Three suggestive examples:

① **Uniformly random number in $\{0, \dots, 255\}$:** $H(X) = \log_2 256 = 8$ bit

② **Poor man's submarine game:** Single submarine hidden, other player asks if submarine in some square \rightarrow hit/miss



1st move: $P(\text{hit}) = \frac{1}{64} \rightarrow h(\text{hit}) = 6$ bit **learned precise location (64 options)**
 $P(\text{miss}) = \frac{63}{64} \rightarrow h(\text{miss}) \approx 0.0224$ bit **learned little (63 remaining)**

2nd move: $P(\text{miss}) = \frac{62}{63} \rightarrow h(\text{miss}) \approx 0.0230$ bit

(if 1st missed) after 32 misses: $\sum h(\text{miss}) = \log \frac{64}{63} + \dots + \log \frac{33}{32} = \log \frac{64}{32} = 1$ bit **localized to 1/2 of squares**

after 48 misses: $\sum h(\text{miss}) = \log \frac{64}{16} = 2$ bit **localized to 1/4 of the squares**

hit in 49th round: $h(\text{hit}) = \log \frac{1}{16} = 4$ bit $\rightarrow \sum = 6$ bit $= H(\text{position})$

More generally: If we hit when n squares remaining

$$\sum h(\text{miss}) + h(\text{hit}) = \log \frac{64}{63} + \dots + \log \frac{n+1}{n} + \log \frac{n}{1} = \log 64 = 6 \text{ bit}$$

③ "Wenglish" has 2^{15} words in $\{A, \dots, Z\}^{25}$ s.t. frequency of single letters matches English. Let w be uniformly random word in this list.

$H(w) = 15$ bit, i.e. on average 3 bit/letter

but e.g. $p(w_1 = z) = 0.1\% \Rightarrow h(w_1 = z) \approx 10$ bit \leftarrow

no contradiction; we learn less info from the rest since few words start with Z

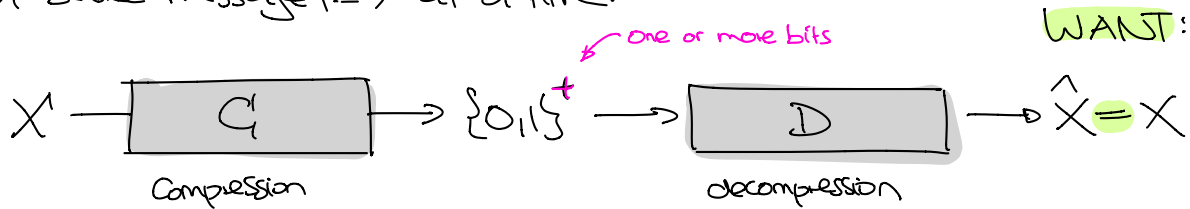
Compression and Symbol Codes (§5)

Consider data source modeled by RV X . Assume we know distribution P_X .

E.g. X could be a letter and we assume $P(x) = P_{\text{English}}(x)$

How well can we compress?

Today + on Thursday we consider Symbol codes, which compress one symbol (letter, source message, ...) at a time:



GOAL: Show that lossless compression one symbol at a time can achieve $H(X) \leq L < H(X) + 1$, where L = average length of codeword.

↑ at least one more bit than entropy

NOTATION: $S^+ = \bigcup_{N \geq 1} S^N$ = nonempty strings over S

$l(w)$ = length of string $w \in S^+$

Symbol code: $C: \mathcal{A} \rightarrow \{0,1\}^+$ for alphabet \mathcal{A}

* average length: $L(C, P) = L(C, X) = \sum_{x \in \mathcal{A}} P(x) l(C(x)) = E[l(C(X))]$
 want to minimize

* extended code: $C^+: \mathcal{A}^+ \rightarrow \{0,1\}^+$, $C^+(x_1 \dots x_n) := C(x_1) \dots C(x_n)$

Two important classes of codes:

* C is called uniquely decodable (UD) if $C^+(w) = C^+(w') \Rightarrow w = w'$ $\forall w, w' \in \mathcal{A}^+$ } we really want this!

* C is called a prefix code if no codeword $C(x)$ is prefix of any other

Any prefix code is UD!