

"Numerical" random variables

If $X \sim P$ is RV with values in $\mathcal{A} \subseteq \mathbb{R}$:

Expectation value (mean): $E[X] = E[X] = \sum_x P(x) \cdot x$

* $E[f(X)] = \sum_x P(x) \cdot f(x)$ "law of the unconscious statistician"

* $E[cX] = c \cdot E[X]$ & $E[X+Y] = E[X] + E[Y]$ (A)

* If X, Y independent: $E[XY] = E[X] \cdot E[Y] = \sum_{x,y} p(x)p(y) xy$

↳ $X \sim \text{Uniform}(\{-1, 1\})$, $Y = -X$ $\stackrel{\text{NOT indep}}{\Rightarrow} E[XY] = -1$, $E[X] = E[Y] = 0$

Variance: $\text{Var}(X) = E[(X - EX)^2]$

$$= \sum_x P(x)(x - EX)^2 = E[X^2] - E[X]^2$$

* $\text{Var}(cX) = c^2 \text{Var}(X)$

* If X, Y independent:

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) \quad (\text{B})$$

↳ we have $E[XY] = E[X] \cdot E[Y]$

Examples

P	Bernoulli(f)	Binomial(n,f)
E	f	n·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 $X \geq 0$: $\Pr(X \geq t) \leq \frac{E[X]}{t} \quad (\text{A})$

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:

$$\Pr(|X - EX| \geq \varepsilon) \leq \frac{\text{Var}(X)}{\varepsilon^2}$$

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

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

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

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

WHP: empirical average
 ≈ expectation value

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

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. $\sum_z P(z)f(z) \geq f\left(\sum_z P(z)z\right)$

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

Entropy (§2.4)

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

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

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

unit "bit"

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

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

$\in [0, 1]$

$$\log \frac{1}{P}$$



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 $p=1$
- * $H(X) \leq \log \#\{x : P(x) > 0\} \leq \log \# \text{dom}_X$ } Pf: Apply Jensen with $f = \log$ and $Z = \frac{1}{P(x)}$:
 $H(X) = \log \# \text{dom}_X \iff X \text{ uniformly random}$ } $E[\log \frac{1}{P(x)}] \leq \log E[\frac{1}{P(x)}]$
 with equality iff $P(X)$ constant, i.e.
 $P(x) > 0, P(y) > 0 \Rightarrow P(x) = P(y)$ \square

* NOTATION: $H(X, Y) = H(XY) = \text{entropy of joint distribution } P(XY)$

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

Pf: Since $P(X, Y) = P(X)P(Y)$ we have $\log \frac{1}{P(X, Y)} = (\log \frac{1}{P(X)}) + (\log \frac{1}{P(Y)})$
 ↳ take expectation values. \square

[Interpretation?] Let us call $h(x) = h(X=x) = \log_2 \frac{1}{P(x)}$ the information content (or "surprise") of an outcome $x \in \text{dom}_X$.
 $\Rightarrow H(X) = E[h(X)]$ is average information content.

Why is this a good definition? Three suggestive examples:

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

A							
B							
C							
D							
E							
F							
G							
H	1	2	3	4	5	6	7

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

1st move: $P(\text{hit}) = \frac{1}{64} \rightarrow h(\text{hit}) = 6 \text{ bit}$ learned precise location (64 options)
 $P(\text{miss}) = \frac{63}{64} \rightarrow h(\text{miss}) \approx 0.022 \text{ bit}$ learned little (63 remaining)

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

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

but e.g. $p(w_1 = Z) = 0.1\% \Rightarrow h(w_1 = Z) \approx 10 \text{ bit}$ ↲

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