

Ex (Filtering)

Let $X \sim N(0, 1)$ be an unknown signal,
corrupted by unknown indep. noise $W \sim N(0, \sigma^2)$.

You observe $Y = X + W$. Estimate X from Y, σ
to minimize the mean-squared error.

$$\bullet \hat{X} := \operatorname{argmin} \{ \mathbb{E}(\hat{X} - X)^2 : \hat{X} \text{ is } \sigma(Y)\text{-mble} \}$$

Gr p.151 $\mathbb{E}[X|Y]$

Remark $\frac{\mathbb{E}[XY]}{\mathbb{E}[Y^2]} \cdot Y = \frac{\mathbb{E}X(X+W)}{\mathbb{E}(X+W)^2} \cdot Y \stackrel{\substack{\text{EX}^2=1, \text{EXW}=0 \text{ (indep)} \\ X+W \sim N(0, 1+\sigma^2)}}{\downarrow} \frac{Y}{1+\sigma^2}$

$$\bullet \text{MSE} = \mathbb{E}(\hat{X} - X)^2 = \mathbb{E}\left(\frac{X+W}{1+\sigma^2} - X\right)^2 = \mathbb{E}\left(\frac{W - \sigma^2 X}{1+\sigma^2}\right)^2 \stackrel{N(0, \sigma^2 + \sigma^4)}{=} \frac{\sigma^2 + \sigma^4}{(1+\sigma^2)^2} = \frac{\sigma^2}{1+\sigma^2}$$

• Interpretation: $\begin{cases} \text{Small noise } (\sigma \rightarrow 0) \Rightarrow \hat{X} \approx Y, \text{MSE} \rightarrow 0 \text{ (trust observation)} \\ \text{Large noise } (\sigma \rightarrow \infty) \Rightarrow \hat{X} = 0, \text{MSE} \rightarrow 1 \text{ (ignore observation)} \end{cases}$

• Normality is essential $\left(X \sim \text{Rademacher}, W \sim \text{Unif}(-1, 1) \right)$
 $\Rightarrow \hat{X} := \operatorname{sign}(X+W) = X$ is exact recovery

HW | extend to n noisy observations

$$Y_i \sim X + W_i$$

Show that $\hat{X} = \frac{\bar{Y}}{1+\bar{\sigma}^2}$ where $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$, $\bar{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \sigma_i^2$

Ex (Predicting a term from a sum)

let X_1, \dots, X_n be iid r.v's, $S_n := X_1 + \dots + X_n$. Then

$$\mathbb{E}[X_i | S_n] = \frac{S_n}{n} \quad \forall i \leq n$$

$\mathbb{E}[X_i | S_n] =: f_i(S_n)$ don't depend on i by symmetry,
and $\sum_1^n f_i(S_n) = \mathbb{E}[S_n | S_n] = S_n \Rightarrow f_i = \frac{S_n}{n}$.

Ex (Predicting a term from many sums)

$$\underline{\underline{\text{Ex}}} \quad \mathcal{F}_n := \sigma(S_n, S_{n+1}, \dots) \Rightarrow \mathbb{E}[X_i | \mathcal{F}_n] = \frac{S_n}{n} \quad \forall i \leq n$$

$$\mathcal{F}_n = \sigma(S_n, X_{n+1}, X_{n+2}, \dots) = \sigma(\underbrace{\sigma(S_n)}_{\mathcal{G}} \cup \underbrace{\sigma(X_{n+1}, \dots)}_{\mathcal{F}})$$

("C" from $S_k = S_n + X_{n+1} + \dots + X_k \quad \forall k \geq n$)
("D" from $X_k = S_k - S_{k-1} \quad \forall k > n$)

$$\Rightarrow \mathbb{E}[X_i | \mathcal{F}_n] \xrightarrow{\text{p. 149 (c')}} \mathbb{E}[X_i | \mathcal{G}] \stackrel{\text{Ex. above}}{=} \frac{S_n}{n}$$

THE LAW OF TOTAL VARIANCE

Def The conditional variance of a r.v. X on a σ -algebra \mathcal{F} is

$$\text{Var}(X|\mathcal{F}) := \mathbb{E} \left[(X - \mathbb{E}[X|\mathcal{F}])^2 | \mathcal{F} \right] \stackrel{\text{check!}}{=} \mathbb{E}[X^2 | \mathcal{F}] - (\mathbb{E}[X | \mathcal{F}])^2$$

(*)

Prop (The Law of Total Variance)

$$\text{Var}(X) = \mathbb{E}[\text{Var}(X|\mathcal{F})] + \text{Var}(\mathbb{E}[X|\mathcal{F}])$$

$$\sqrt{\cdot} \cdot \mathbb{E}[X^2] \stackrel{\text{LTP}}{=} \mathbb{E}[\mathbb{E}[X^2 | \mathcal{F}]] \stackrel{(*)}{=} \mathbb{E}[\text{Var}(X | \mathcal{F}) + \underbrace{(\mathbb{E}[X | \mathcal{F}])^2}_{Z}]$$

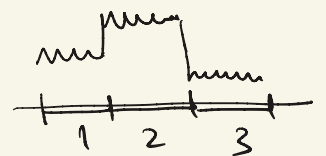
$$\bullet (EX)^2 \stackrel{LTP}{=} (EZ)^2$$

Subtract $\Rightarrow \text{Var}(X) = \mathbb{E}[\text{Var}(X|F)] + \underbrace{\mathbb{E}[Z^2] - (\mathbb{E}Z)^2}_{\text{Var}(Z)}$

Ex: Sample a random student in a calculus class

X = student's exam score

Y = student's group number (e.g. 1, 2, 3)



$$\Rightarrow \text{Var}(X) = \mathbb{E} \text{Var}(X|Y) + \text{Var}(\mathbb{E}[X|Y])$$

"within-group variance" + "between-group variance"

HW: True/false?

- $\text{Var}(X) \geq E[\text{Var}(X|F)]$

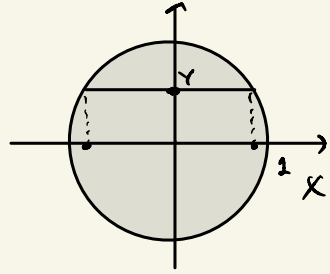
$$\cdot \text{Var}(X) \geq \text{Var}(X|F) \text{ a.s.}$$

HW: state, prove the Law of Total Covariance

Conditional distributions

Intuitive examples:

- $X|Y = \left\{ \begin{array}{l} 2Y \text{ with prob } 1/2 \\ Y/2 \text{ with prob } 1/2 \end{array} \right\}$ in the Exchange Paradox.
- $X|Y \sim$ distribution of income (X) in a given country (Y)
- $Y \sim \text{Unif}[0,1]; \quad X|Y \sim N(0, Y^2)$.
- $(X,Y) \sim \text{Unif}(\text{unit disc}) \Rightarrow X|Y \sim \text{Unif}(-\sqrt{1-Y^2}, \sqrt{1-Y^2})$



- Heuristic def: the conditional distr. " $X|\mathcal{F}$ " is the random prob. meas.

$$\mu(B) := P\{X \in B | \mathcal{F}\} := E[1_{\{X \in B\}} | \mathcal{F}], \quad B \in \mathcal{B}(\mathbb{R}).$$

- Slight issue: defined a.s. — up to a null set.

The null set may depend on $B \Rightarrow$ not clear why prob.-measure.

However, this issue can be fixed:

Thm (^{regular} Conditional distributions) let X be a r.v. and $\mathcal{F} \subset \Sigma$ be a σ -algebra.

Then $\forall B \in \mathcal{B}(\mathbb{R}), \forall \omega \in \Omega \quad \exists \mu(B, \omega)$ such that:

(i) $\forall \omega \in \Omega: \quad B \mapsto \mu(B, \omega)$ is a probability measure on $\mathcal{B}(\mathbb{R})$

(ii) $\forall B \in \mathcal{B}(\mathbb{R}): \quad \mu(B, \omega) \stackrel{\text{a.s.}}{=} P\{X \in B | \mathcal{F}\}(\omega)$ ("conditional distr." of X given \mathcal{F})

Proof If Thm holds, $\forall \omega \in \Omega$ the cdf of $\mu(\cdot, \omega)$ must be

$$F(x, \omega) = \mu(-\infty, x] \stackrel{\text{a.s.}}{=} \mathbb{P}\{X \leq x | \mathcal{F}\}(\omega) = \mathbb{E}[\mathbb{1}_{\{X \leq x\}} | \mathcal{F}](\omega).$$

So, let's define the function

$$F(r, \omega) := \mathbb{E}[\mathbb{1}_{\{X \leq r\}} | \mathcal{F}](\omega) \quad \forall r \in \mathbb{Q} \quad (o)$$

\uparrow \forall version.

- Excluding null sets, we can find a "nice" set $A \subset \Omega$ with $\mathbb{P}(X \in A) = 1$ and such that $\forall \omega \in A$ we have:

(a) $F(r, \omega) < F(s, \omega) \quad \forall r < s \text{ in } \mathbb{Q}$ (by monotonicity of cond \mathbb{E})

(b) $F(r + \frac{1}{n}, \omega) \downarrow F(r, \omega)$ as $n \rightarrow \infty$, $\forall r \in \mathbb{Q}$ (by cond MCT)

(c) $F(-n, \omega) \rightarrow 0$, $F(n, \omega) \rightarrow \infty$ as $n \rightarrow \infty$ (by cond MCT)

- For each $\omega \in A$, extend (o) to \mathbb{R} by defining

$$F(x, \omega) := \inf \{ F(r, \omega) : r > x, r \in \mathbb{Q} \} \quad \forall x \in \mathbb{R} \quad (oo)$$

(Properties (a), (c) show agreement on \mathbb{Q}).

And for each $\omega \notin A$, let F be some fixed cdf, e.g.

$$F(x, \omega) := \Phi(x) \quad \forall x \in \mathbb{R}$$

\uparrow $N(0,1)$

- F is monotonely nondecreasing (by def oo),
has the correct limits (0 at $-\infty$, 1 at ∞) (by (c)),
and is right-continuous (by (b), def oo & monotonicity - check!)

$$\Rightarrow \forall \omega \in \Omega: \quad x \mapsto F(x, \omega) \text{ is a CDF}$$

$$\Rightarrow \forall \omega \in \Omega: \quad \exists \text{ Borel prob measure } B \mapsto \mu(B, \omega) \text{ with cdf } x \mapsto F(x, \omega).$$

• It remains to prove (ii), i.e. check that $\forall B \in \mathcal{B}(\mathbb{R})$:

(i) the r.v. $\omega \mapsto \mu(B, \omega)$ is \mathcal{F} -mble

$$(ii) \int_E \mu(B, \omega) dP(\omega) = \int_E \mathbb{1}_{\{X(\omega) \in B\}} dP(\omega) \quad \forall E \in \mathcal{F}$$

(i) $\mathcal{L} := \{B \in \mathcal{B}(\mathbb{R}) : \omega \mapsto \mu(B, \omega) \text{ is } \mathcal{F}\text{-mble}\}$

is a λ -system $\left(\begin{array}{l} \mu(\cdot, \omega) \text{ is a prob-meas} \Rightarrow \mu(\bigcup_{i=1}^{\infty} B_i, \omega) = \sum_{i=1}^{\infty} \mu(B_i, \omega) \\ \Rightarrow \text{if each function in RKS is } \mathcal{F}\text{-mble} \Rightarrow \text{LKS is } \mathcal{F}\text{-mble} \end{array} \right)$

that contains the π -system $\mathcal{P} := \{(-\infty, r], r \in \mathbb{Q}\}$ by (o)

π - λ theorem $\Rightarrow \sigma(\mathcal{P}) \subset \mathcal{L}$ ✓
 $\quad \quad \quad \mathcal{B}(\mathbb{R})$

(ii) Fix $\forall E \in \mathcal{F}$. Each side of (ii) defines a finite measure of B (by MCT), and identity (ii) holds $\forall B \in \mathcal{P}$ by (o):

$$\int_E \mu((-\infty, r], \omega) dP(\omega) = \int_E F(r, \omega) dP(\omega) \stackrel{\substack{\text{by (o) \& def of} \\ \text{condit. exp.}}}{=} E[\mathbb{1}_{\{X \leq r\}} \mathbb{1}_E].$$

By the uniqueness of measures (or by applying π - λ theorem),

(ii) holds $\forall B \in \mathcal{B}(\mathbb{R})$. □

Hw Extend the thm for r. vectors $X \in \mathbb{R}^n$ e.g. for $n=2$, work with $\{x \leq x, y \leq y\}$ instead of $\{x \leq x\}$

Hw (The expectation of the conditional distr = conditional expectation)

Let μ_ω be the conditional distr. of X given \mathcal{F} , $h: \mathbb{R} \rightarrow \mathbb{R}$ integrable

Show that $\int h(x) d\mu_\omega(x) \stackrel{\text{a.s.}}{=} E[h(X) | \mathcal{F}](\omega)$



Conditional densities

- When $\mathcal{F} = \sigma(Y)$, we write $X|Y$ instead of $X|\sigma(Y)$

Prop (Conditional density) If (X, Y) has density $f_{X,Y}(x,y)$, then the conditional distr. of X given Y has density $x \mapsto f_{X|Y}(x|y)$, where

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}, \quad x \in \mathbb{R}$$

Proof. $x \mapsto f_{X|Y}(x|y)$ is indeed a density $\forall y$ (total integral = 1)

- It remains to check that the cond. exp. indeed has this density, i.e.

$$\forall B \in \mathcal{B}(\mathbb{R}): \quad P\{X \in B | Y\} \stackrel{\text{a.s.}}{=} \int_B f_{X|Y}(x, Y) dx \quad \text{a.s. (in } Y)$$

$$= E[1_{\{X \in B\}} | \sigma(Y)]$$

def of cond. exp. $\left\{ \begin{array}{l} \int_B f_{X|Y}(x, Y) dx \text{ is } \sigma(Y)\text{-measurable? Yes! (it's a function of } Y) \\ E[1_{\{X \in B\}} 1_F] \stackrel{?}{=} E\left(\left(\int_B f_{X|Y}(x, Y) dx\right) 1_F\right) \quad \forall F \in \sigma(Y) \end{array} \right.$

$$P\{X \in B, Y \in R\} \stackrel{?}{=} \int_R \left(\int_B f_{X|Y}(x, y) dx \right) f_Y(y) dy$$

$$\stackrel{!}{=} \int_{R \times B} f(x, y) dx dy \quad \text{Yes!} \quad \square$$

Remark $f_{X|Y} = \frac{f_{X,Y}}{f_Y}$ is a "continuous version" of $P(E|F) = \frac{P(E \cap F)}{P(F)}$
 Allows to condition on events $\{Y=y\}$ of measure 0 ☺

SKIP: "Continuous" version of LTP: $f_X(x) \stackrel{\text{Lec 10}}{=} \int_{-\infty}^{\infty} f(x, y) dy \stackrel{\text{Prop}}{=} \int_{-\infty}^{\infty} f_{X|Y}(x|y) f_Y(y) dy$

\Rightarrow "Continuous" Bayes formula:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{f_{Y|X}(y|x) f_X(x)}{f_Y(y)}$$

(Williams 15.7)

- Remarks
1. Extensions for vectors X, Y - obvious.
 2. For discrete X, Y , the same formulas hold for pmfs (easier!)

Application: revisit the filtering problem (p.152.5):

Signal $X \sim N(0, 1)$
noise $W \sim N(0, \sigma^2)$ indep
observation $Y = X + W$.
 $X|Y = ?$

Solution: Let's apply Bayes formula.

$$f_X(x) = \text{pdf of } N(0, 1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$$

$$f_{Y|X}(y|x) = \text{pdf of } N(x, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(y-x)^2}{2\sigma^2}\right]$$

$$\begin{aligned} \Rightarrow \log f_{X|Y}(x|y) &= \log f_{Y|X}(y|x) + \log f_X(x) + c_1(y) \\ &= -\frac{(y-x)^2}{2\sigma^2} - \frac{x^2}{2} + c_2(y) \\ &= -\frac{1+\sigma^2}{2\sigma^2} \left(x - \frac{y}{1+\sigma^2}\right)^2 + c_3(y) \quad (\text{complete the square}) \end{aligned}$$

$$\Rightarrow f_{X|Y}(x|y) = \text{pdf of } N\left(\frac{y}{1+\sigma^2}, \frac{\sigma^2}{1+\sigma^2}\right)$$

$$\Rightarrow \text{the best estimator is } \hat{X} = \frac{Y}{1+\sigma^2}. \text{ Its } \text{MSE} = \text{Var}(\hat{X}) = \frac{\sigma^2}{1+\sigma^2}$$

We recovered the result on p.152.5.

APPLICATION: LIKELIHOOD RATIO TEST

Hypothesis test:

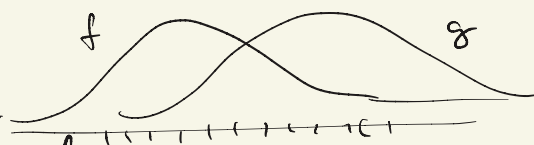
- Given iid observations X_1, \dots, X_n , which of the two given distributions have they been sampled from?

- let's say, one has pdf f and the other, g

- Model: $\theta \sim \text{Ber}(1/2)$. Conditionally on θ ,

If $\theta = 0 \Rightarrow$ draw $x = (X_1, \dots, X_n)$ from f

If $\theta = 1 \Rightarrow$ from g .



- Test: compute the likelihood ratio

$$\Lambda(x) := \frac{P\{\theta=0|x\}}{P\{\theta=1|x\}}$$

Output "f" if $\Lambda(x) \geq 1$ and "g" if $\Lambda(x) < 1$

- How to compute $\Lambda(x)$? Bayes:

$$P\{\theta=0|x=x\} = \frac{P\{X=x|\theta=0\} \cdot P\{\theta=0\}}{P\{X=x\}}, \quad x = (x_1, \dots, x_n) \in \mathbb{R}^n$$

and similarly for $P\{\theta=1|x=x\}$. Divide \Rightarrow

$$\frac{P\{\theta=0|x=x\}}{P\{\theta=1|x=x\}} = \frac{P\{X=x|\theta=0\}}{P\{X=x|\theta=1\}} = \frac{f(x_1) \dots f(x_n)}{g(x_1) \dots g(x_n)}$$

Thus (by "conditioning = fixing" before) \Rightarrow

$$\Lambda(x) = \frac{f(x_1) \dots f(x_n)}{g(x_1) \dots g(x_n)}$$

(i.e. "choose f or g , whichever makes the sample x_1, \dots, x_n more likely")

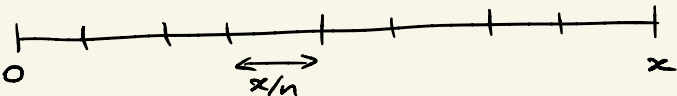
Remarks 1. For pdf's - the same -

2. LRT is the best test (Neyman-Pearson lemma)

3. Works for > 2 hypotheses: choose the one that maximizes the likelihood of sample (MLE).

Ex | X = time of the first call at a police station after midnight.
Distribution of X ?

cdf $F(a) = P\{X \leq x\} = ?$



Divide $[0, x]$ into n intervals of length x/n .

$P\{\text{call during a given interval}\} = \lambda \cdot \frac{x}{n}$ (proportional to the length of the interval)

$\Rightarrow P\{X > a\} = P\{\text{no call in } [0, x]\}$
 $= P\{\text{no call in any of the intervals}\}$

coefficient of proportionality

$$= \left(1 - \frac{\lambda x}{n}\right)^n \longrightarrow e^{-\lambda x} \text{ as } n \rightarrow \infty$$

Thus, $P\{X > x\} = e^{-\lambda x}, \quad x > 0$



Def A r.v. X has the exponential distribution with parameter λ if
 $P\{X > x\} = e^{-\lambda x}, \quad x > 0.$

Notation: $X \sim \text{Exp}(\lambda)$. The parameter λ is called the rate.

• pdf: $f(x) = \frac{d}{dx}(1 - e^{-\lambda x}) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$

• $EX = \int_0^{\infty} x e^{-\lambda x} dx = \boxed{\frac{1}{\lambda}}, \quad \text{Var}(X) = \boxed{\frac{1}{\lambda^2}} \quad (\text{Dir})$

• Exponential distribution is used to model waiting times
 (lifetime of iPhone, time until next customer arrives, etc.)

SKIP

Prop (Memoryless property) $X \sim \text{Exp}(\lambda)$ satisfies

$$P\{X > t+s | X > t\} = P\{X > s\} \quad \forall s, t > 0$$

$$\left[\text{LHS} = \frac{P\{X > t+s\}}{P\{X > t\}} = \frac{e^{-\lambda(t+s)}}{e^{-\lambda t}} = e^{-\lambda s} = \text{RHS} \right]$$

\uparrow $P\{\text{wait} > s \text{ more minutes}\}$ \uparrow $P\{\text{wait} > s \text{ minutes}\}$
 \uparrow def

• i.e. $X \sim \text{Exp}(\lambda) \Rightarrow X - t | X \geq t \sim \text{Exp}(\lambda)$

• Ex 1 let $X_i \sim \text{Exp}(\lambda_i)$, $i=1,2$, be independent.

$$(a) P\{X_1 \leq X_2\} = E_{X_1}[X_1 \leq X_2 | X_1] = E_{X_1}[e^{-\lambda_2 X_1}] = \int_0^{\infty} e^{-\lambda_2 x} \cdot \overbrace{\frac{-\lambda_1}{1} e^{-\lambda_1 x}}^{\text{pdf of } X_1} dx = \frac{\lambda_1}{\lambda_1 + \lambda_2}$$

tail of X_2

$$(b) \min(X_1, X_2) \sim \text{Exp}(\lambda_1 + \lambda_2)$$

$$\left[P\{\min(X_1, X_2) > t\} = P\{X_1 \geq t, X_2 \geq t\} \stackrel{\text{indep}}{=} e^{-\lambda_1 t} e^{-\lambda_2 t} = e^{-(\lambda_1 + \lambda_2)t} \right]$$

induction \Rightarrow Cor $\min(X_1, \dots, X_n) \sim \text{Exp}(\lambda_1 + \dots + \lambda_n)$ (Min-stability)

Ex 2 You arrive at a post office having 2 clerks; both are busy; no line.

You enter the service when either clerk becomes free.

The service times of clerks are $\text{Exp}(\lambda_1)$, $\text{Exp}(\lambda_2)$

Find the expected time you spend in the office.

$R_i :=$ remaining service time of the customer with clerk i
 $\sim \text{Exp}(\lambda_i)$ by memoryless property.

$S :=$ your service time. $T = \min(R_1, R_2) + S \Rightarrow$

$$ET = E \min(R_1, R_2) + ES = \frac{1}{\lambda_1 + \lambda_2} + ES.$$

$\sim \text{Exp}(\lambda_1 + \lambda_2)$ (Ex 1b)

$$ES = E[S | R_1 < R_2] P\{R_1 < R_2\} + E[S | R_2 \leq R_1] P\{R_2 \leq R_1\} = \frac{2}{\lambda_1 + \lambda_2} \Rightarrow ET = \frac{3}{\lambda_1 + \lambda_2}$$

$\underbrace{E[S | R_1 < R_2]}_{\substack{\text{Exp}(\lambda_1) \\ S \sim 1/\lambda_1}} \underbrace{P\{R_1 < R_2\}}_{\substack{\frac{\lambda_1}{\lambda_1 + \lambda_2} \text{ (Ex 1a)}}} + \underbrace{E[S | R_2 \leq R_1]}_{\substack{\text{Exp}(\lambda_2) \\ S \sim 1/\lambda_2}} \underbrace{P\{R_2 \leq R_1\}}_{\substack{\frac{\lambda_2}{\lambda_1 + \lambda_2} \text{ (Ex 1a)}}}$

E_x (Geometric distribution)

$X \sim \text{Geom}(p)$

if $X = \#$ of the first success in independent trials (each = success with prob. p).

~~$E[X] = \overset{S}{1} \cdot p + \overset{FS}{2} (1-p)p + \overset{FFS}{3} (1-p)^2 p + \overset{FFFS}{4} (1-p)^3 p + \dots = \frac{1}{p}$ (check!)~~

• Alternative computation:

Condition on 1st trial, use L.T.E:

$$E[X] = \underbrace{E[X|S]}_1 \cdot \underbrace{P(S)}_p + \underbrace{E[X|F]}_{\uparrow} \cdot \underbrace{P(F)}_{1-p}$$

$X|F = X+1$ in distribution:

after 1 failure, the experiment resets.

$$\Rightarrow E[X|F] = 1 + E[X]$$

$$\Rightarrow E[X] = p + (1 + E[X])(1-p). \quad \text{Solving yields}$$

$$E[X] = \frac{1}{p}$$

SKIP

Also memoryless (check!)

E_x The only memoryless r.v. with continuous distr. is $\text{Exp}(\cdot)$

The only memoryless r.v. with discrete distr. is $\text{Geom}(\cdot)$

HW

Ex (Coupon collector's problem)

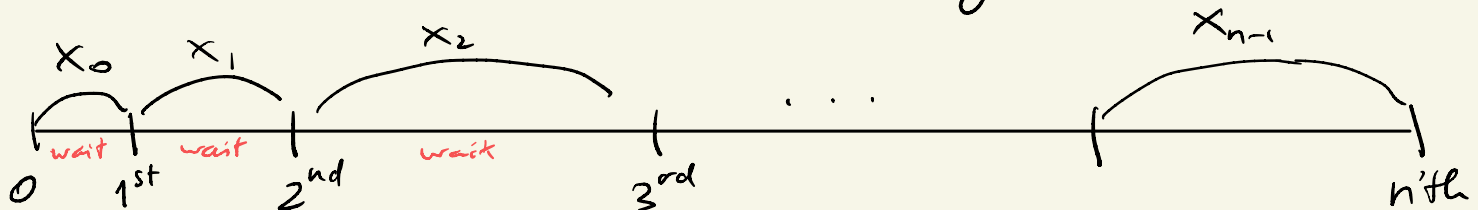
What is the expected number of coupons one needs to collect before obtaining a complete collection of all n types of coupons?

(Assume: each time one obtains a coupon, it is equally likely to be one of n types)

where

$$X = X_0 + X_1 + \dots + X_{n-1}$$

X_i = # additional coupons (after i types have been collected) in order to obtain a new type



$$E[X] = E[X_0] + E[X_1] + \dots + E[X_{n-1}]$$

$X_i \sim ?$ After i coupons have been collected, each coupon we obtain is of a new type with probability

$$p_i = \frac{n-i}{n}$$

← # new types
← # all types

Hence $X_i \sim \text{Geom}(p_i) \Rightarrow E[X_i] = \frac{1}{p_i}$

$$E[X] = \frac{1}{p_0} + \frac{1}{p_1} + \dots + \frac{1}{p_{n-1}} = \frac{n}{n} + \frac{n}{n-1} + \dots + \frac{n}{1} = \boxed{n \left(1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n} \right)}$$

Asymptotic analysis: $\sum_{k=1}^n \frac{1}{k} \approx \int_1^n \frac{dx}{x} = \ln(x) \Big|_1^n = \ln(n)$

$\Rightarrow \boxed{E[X] \approx n \ln n}$ Logarithmic oversampling.