

Distributions	Joint & conditional prob.	Moments																
Bernoulli: $X \sim \text{Bernoulli}(p)$ $P(X=0) = p$ $E[X] = p$ $P(X=1) = (1-p)$ $\text{Var}(X) = p(1-p)$	$P_{X Y} = \frac{P[X=x, Y=y]}{P[Y=y]} = \frac{P_{X,Y}(x,y)}{P_Y(y)}$ $P_{X,Y} = P_Y(y) P_{X Y}(x y)$ $f_X(x) = \int_{-\infty}^{\infty} f_Y(y) f_{X Y}(x y) dy$ $f_X(x) = \sum_{i=1}^n f_{X A_i}(x) P(A_i)$ $f_X(x) = \int f(x,y) dy$ $= \sum_y P(X=x, Y=y)$	$M_x(s) = E[e^{sX}] = 1 + sE[X] + \frac{s^2}{2!} E[X^2]$ $\left(\frac{d^n}{ds^n} E[e^{sX}]\right)(0) = E[X^n]$ $M_x(0) = 1$ $G_x(z) = M_x(zm), M_x(s) = G_x(e^s)$ $\left(\frac{d^n}{ds^n} G_x(z)\right)(0) = P(X=n)$																
Binomial: $X \sim \text{Bin}(n, p)$ $P(X=i) = \binom{n}{i} p^i (1-p)^{n-i}$ $i = 0, \dots, n$ $E[X] = np$ $\text{Var}(X) = np(1-p)$																		
(Geometric: $X \sim \text{geo}(p)$ ) $P(X=i) = (1-p)^{i-1} p$ $i = 1, 2, \dots$ $E[X] = \frac{1}{p}$ $\text{Var}(X) = \frac{1-p}{p^2}$ $P(X \leq x) = 1 - (1-p)^x$																		
Poisson: $X \sim \text{poisson}(\lambda)$ $P(X=i) = \frac{\lambda^i}{i!} e^{-\lambda}$ $i = 0, 1, \dots$ $E[X] = \lambda$ $\text{Var}(X) = \lambda$ $X \sim \text{poisson}(\lambda)$ $Y \sim \text{poisson}(\mu)$ $(X+Y) \sim \text{poisson}(\lambda+\mu)$	Bayes & conditional Bayes $P(A B) = \frac{P(B A)P(A)}{P(B)}$ $f_Y(y) f_{X Y}(x y) = f_X(x) f_{Y X}(y x)$																	
Exponential: $X \sim \text{exp}(\lambda)$ $f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & \text{otherwise} \end{cases}$ $F_X(x) = 1 - e^{-\lambda x}$ $E[X] = \frac{1}{\lambda}$ $\text{Var}(X) = \frac{1}{\lambda^2}$ $X \sim \text{exp}(\lambda)$ $Y \sim \text{exp}(\mu)$ $\min(X, Y) \sim \text{exp}(\lambda + \mu)$ $P(X \leq Y) = \frac{\lambda}{\lambda + \mu}$	Random Variable as func. of another $Y = g(X)$ if $g$ is differentiable and invertible, we have $f_Y(y) = f_X(g^{-1}(y)) \frac{1}{ g'(g^{-1}(y)) }$ $Z = X+Y : f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_{Y X}(z-x) dx$ $= \sum_x P(X=x) P(Y=z-x)$	When $X$ is nonnegative, discrete $\lim_{s \rightarrow -\infty} (M_x(s)) = P(X=0)$ $Y = aX + B \Rightarrow M_Y(s) = e^{Bs} M_X(as)$ $Z = \sum_i X_i \Rightarrow M_Z(s) = \prod_i M_{X_i}(s)$ $\text{indep.}$ $M_Z(s) = \sum_{n=0}^{\infty} (M_X(s))^n P(N=n)$																
Discrete uniform $X \sim \text{Unif}\{a, a+1, \dots, b\}$ $E[X] = \frac{a+b}{2}$ $\text{Var}(X) = \frac{(b-a)(b-a+1)}{12}$ $f(x) = \frac{1}{b-a}$ $F_X(x) = \frac{x-a}{b-a}$	Variance & expectation $E[X] = \sum x f_X(x) = \sum x P(X=x)$ $\text{Var}(X) = E[(X-E[X])^2]$ $E[X A] = \sum_{x A} x f_{X A}(x) dx$ $E[g(X) A] = \sum g(x) f_{X A}(x) dx$ $\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$	Known MGFS																
Continuous uniform $X \sim \text{Unif}(a, b)$ $E[X] = \frac{a+b}{2}$ $\text{Var}(X) = \frac{(b-a)^2}{12}$ $f(x) = \frac{1}{b-a}$ $F_X(x) = \frac{x-a}{b-a}$	<table border="1"> <thead> <tr> <th>Distribution</th><th>MGF</th></tr> </thead> <tbody> <tr> <td>Bernoulli(<math>p</math>)</td><td><math>(1-p) + pe^s</math></td></tr> <tr> <td>Bin(<math>n, p</math>)</td><td><math>(1-p + pe^s)^n</math></td></tr> <tr> <td>Geo(<math>p</math>)</td><td><math>\frac{pe^s}{1 - (1-p)e^s}</math></td></tr> <tr> <td>Poisson(<math>\lambda</math>)</td><td><math>e^{\lambda(e^s - 1)}</math></td></tr> <tr> <td>exp(<math>\lambda</math>)</td><td><math>\frac{\lambda}{\lambda-s}</math>    <math>\lambda &gt; s</math></td></tr> <tr> <td>Unif(<math>a, b</math>)</td><td><math>\frac{e^{bs} - e^{sa}}{s(b-a)}</math></td></tr> <tr> <td><math>N(\mu, \sigma^2)</math></td><td><math>e^{\mu s + \frac{\sigma^2 s^2}{2}}</math></td></tr> </tbody> </table>	Distribution	MGF	Bernoulli( $p$ )	$(1-p) + pe^s$	Bin( $n, p$ )	$(1-p + pe^s)^n$	Geo( $p$ )	$\frac{pe^s}{1 - (1-p)e^s}$	Poisson( $\lambda$ )	$e^{\lambda(e^s - 1)}$	exp( $\lambda$ )	$\frac{\lambda}{\lambda-s}$ $\lambda > s$	Unif( $a, b$ )	$\frac{e^{bs} - e^{sa}}{s(b-a)}$	$N(\mu, \sigma^2)$	$e^{\mu s + \frac{\sigma^2 s^2}{2}}$	Covariance: $\text{cov}(X, Y) = E[(X-\mu_X)(Y-\mu_Y)]$
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Normal: $X \sim N(\mu, \sigma^2)$ $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ $X \sim N(\mu, \sigma^2)$ $Z = \frac{X-\mu}{\sigma} \sim N(0, 1)$ $f_Z(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$ $X \sim N(0, \sigma^2) \Rightarrow E[X^{2N}] = \sigma^{2N} (2n+1)!!$ $X \sim N(\mu_X, \sigma_X^2)$ $Y \sim N(\mu_Y, \sigma_Y^2)$ $X+Y \sim (N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2))$ $dX + c \sim N(\mu_X + c, \sigma_X^2)$	$\text{Var}(Y) = \sum_i \text{Var}(X_i) + 2 \sum_{i>j} \text{Cov}(X_i, X_j)$ for $X_i \sim \text{Bernoulli}(p_i)$ , $E[Y^2] = \sum_i E[X_i^2] + 2 \sum_{i>j} E[X_i X_j]$ if $X_i$ indep $= \sum_i p_i + 2 \sum_{i>j} p_i p_j$ if iid, $= np + n(n-1)p^2$	$\text{Cov}(X, X) = \text{Var}(X)$ $\text{Cov}(aX_1 + bX_2, cY_1 + dY_2)$ distribute each like for all $= ac \text{Cov}(X_1, Y_1) + ad \text{Cov}(X_1, Y_2)$ $+ bc \text{Cov}(X_2, Y_1) + bd \text{Cov}(X_2, Y_2)$ indep $\Rightarrow \text{Cov} = 0$																

Classic problems	Expectation cont.	correlation
<p>Ballot: A scores <math>n</math> B scores <math>m</math> s.t. <math>m &lt; n</math></p> <p><math>P(A</math> strictly ahead of <math>B</math> always) = <math>\frac{n-m}{m+n}</math></p> <p>Gambler ruin: start at <math>i</math> and move +1 or -1 with prob <math>p</math> &amp; <math>1-p</math> respectively. <math>P(C</math> reaching <math>n</math> before 0) is <math>1 - \frac{p}{1-p}^{n-i}</math></p> <p>Secretary: reject first <math>m</math> candidates, take first better than all prev. optimal <math>m = \frac{n}{e}</math></p> <p>Coupon collector: <math>E(T) = n \sum_{i=1}^n \frac{1}{i}</math>; trials needed to collect all coupons</p> <p>Derangement: <math>P(X=n) = n! \sum_{k=0}^n \frac{1}{k!}</math></p> <p>Neg geometric: <math>B</math> bad (<math>N</math> good), number of draws till <math>r</math>th good item? <math>P(X=r) = \frac{(x-1)(N-x)}{(r-1)(G-r)}</math></p> <p><math>E[X] = \frac{N+1}{G+1} C_N^G</math></p> <p><math>Var(X) = \frac{B(G(N+1))}{(G+1)^2(G+2)}</math></p>	<p><math>E[X] = \sum_{k=1}^{\infty} P(X \geq k) = \int_0^{\infty} P(X \geq x) dx</math></p> <p>useful series</p> $\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x$ $\sum_{k=0}^{\infty} r^k = \frac{1}{1-r} \quad  r  < 1$ $\sum_{k=0}^{\infty} r^k = \frac{(-r)^{n+1}}{1-r}, r \neq 1$ <p>Triangle q. from HW:</p> <p>(i) <math>2 \int_0^{1/2} x dx = \frac{1}{4}</math></p> <p>(ii) <math>\int_0^{1/2} \frac{x}{1-x} dx = \ln 2 - \frac{1}{2}</math></p> <p>(iii) <math>2(\ln 2 - \frac{1}{2})</math></p> <p>for <math>S = \sum_i^N X_i \quad X_i \stackrel{iid}{\sim} \exp(\lambda)</math></p> <p><math>N \sim \text{geo}(p)</math></p> <p><math>S \sim \exp(\lambda p)</math></p> <p>for gaussian confidence interval:</p> <p><math>P( \bar{X} - \mu  \leq x) = \Phi(x) - \Phi(-x)</math></p> <p>* <math>p</math> confidence interval solve for <math>p</math></p> <p>for num trials needed, <math>\bar{X} \pm \frac{x}{\sqrt{n}}</math> <math>x</math> is got by solving confidence interval</p> <p><math>\frac{x}{\sqrt{n}} \leq \text{num samples}</math></p>	$P(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_x \sigma_y}$ <p>Finding PDF min/max</p> <p>if <math>X \sim \text{geo}(p)</math> <math>\text{E}[X] = p^{-1}</math></p> <p><math>\min(X, Y) \sim \text{geo}(p+q-pq)</math></p> <p>if <math>X_i \stackrel{iid}{\sim} \text{geo}(p)</math></p> <p><math>\min(X_i) \sim \text{geo}(1-(1-p)^n)</math></p> <p>if <math>X_i \sim \exp(\lambda_i)</math></p> <p><math>\min(X_i) \sim \exp(\sum \lambda_i)</math></p> <p>if not geo or poisson</p> <p>min: <math>P(X, Y &gt; t)</math></p> <p>Max: <math>P(X, Y &lt; t)</math></p> <p>Extra dists.</p> <p>Erlang: sum of <math>k</math> i.i.d. <math>\exp(\lambda)</math></p> <p><math>E[X] = \frac{k}{\lambda} \quad \text{Var}(X) = \frac{k}{\lambda^2}</math></p> <p><math>f(x) = \frac{\lambda^k}{k!} x^{k-1} e^{-\lambda x} \quad F(x) = 1 - \sum_{i=0}^k \frac{e^{-\lambda x}}{i!} \lambda^i</math></p> <p><math>X \sim \text{Erlang}(k, \lambda) \quad \alpha X \sim \text{Erlang}(k, \frac{\lambda}{\alpha})</math></p> <p>Pascal: sum of <math>k</math> i.i.d. <math>\text{Geo}(p)</math></p> <p><math>E[X] = \frac{k}{p} \quad \text{Var}(X) = \frac{k(1-p)}{p^2}</math></p> <p><math>f(x) = \binom{x-1}{k-1} p^k (1-p)^{x-k} \quad x \in \{k, k+1, \dots\}</math></p> <p><math>F(x) = P(X \leq x) = \sum_{i=k}^x \binom{i-1}{k-1} p^k (1-p)^{i-k}</math></p> <p>convergence</p> <p>(1) <math>\lim_{n \rightarrow \infty} P( Y_n - X  &gt; \epsilon) = 0</math></p> <p style="text-align: right;">* try using log, seen or Chebychev's.</p> <p>(2) <math>P(\lim_{n \rightarrow \infty} X_n = x) = 1</math></p> <p>Borel cond: <math>\mathbb{E}[P(A_n) \infty : A_n \text{ occurs finite many times}] \quad \mathbb{E}[P(A_n) \infty : A_n \text{ occurs infinitely often almost surely}]</math></p>

Concentration inequality.

Markov:  $P(X \geq c) \leq \frac{E[X]}{c} < 0$   
for non-neg RV  $X$  w/ finite mean  
Chebyshev:  
 $P(|X - \mu| \geq c) \leq \frac{\text{var}(X)}{c^2}$   
 $P(|X - \mu| \geq kc) \leq \frac{1}{k^2}$

Markov chains

- to show is Markov Chain, show memorylessness
- states:  
transient  $P(\text{return}) = 0$  ex: chains w/ absorbing state (state itself poss. recurrent & states it can reach transient)

null recurrent:  $P(\text{return}) = 1$  and  $E[\text{return time}] = \infty$  ex: symmetric random walk

pos recurrent:  $P(\text{return}) = 1$  and  $E[\text{return time}] < \infty$ . If a chain is finite & irreducible it is pos recurrent

If a chain is irreducible we have  $E[\text{return time to } i \text{ from } j] = \frac{1}{\pi_j}$ .  
For random walks on undirected graph where you move uniformly to neighbor  $\pi_i = \frac{1}{\deg(i)}$

Can you use detailed balance?  
if yes, try  $\pi_{ij} = \frac{p_{ij}}{p_{ji}}$

Poisson processes

Both forward AND backward interarrival times are exp  
problem solving: in competing poisson process problems, you can simplify into 1 type of event and then look at prob that the event is classified as either type

$$\sum_{X \in M}$$

Given  $n$  events happened in some interval, they are uniformly distributed. If ordered, they will evenly distribute

Statistical inference

MLE estimation:

We find  $\max_{\theta} p(x|\theta)$  which is

$\max_{\theta} p(x_1, \dots, x_n | \theta)$ . Maybe take log to simplify. Then differentiate to find max

MAP estimation:

Want  $p(\theta | X)$ . Assume you have prior  $p(\theta)$ . Then  $p(\theta | X) \propto p(X|\theta) p(\theta)$ . Plug in, differentiate & set to 0 to find max

Decision functions:

(1) setup: write out  $H_0$  &  $H_1$ ,

(2) find  $\Delta(x) = \frac{f_1(x)}{f_0(x)}$ . If

this is inc. in  $x$ , we will have  $S(x) = \begin{cases} 1 & x > c \text{ rej. } H_0 \\ 0 & x \leq c \text{ accept } H_0 \end{cases}$

(3) Usually we will have some bound on PFA =  $P(\hat{x} = 1 | X=0) = \alpha$ . Write this in terms of decision boundary.

(4) if necessary randomize at boundary. We need to hit it exactly. Write equation of the form  $P(\text{rej.}) = P(X > b+) + rP(X=b)$  where we will rej. at boundary w/ prob  $r$ . note this inequality may be flipped if  $\Delta$  dec in  $x$

Statistical inference cont.  
If  $\Delta(x)$  is not monotonic then rej.  $H_0$  on sets where  $\Delta(x)$  is largest. Randomize at last point if necessary.

MMSE problems: we want to find  $\hat{x}$  from  $Y$  by  $\min E[(X - \hat{X}(Y))^2]$ . This is  $\hat{X}_{\text{mean}}(Y) = E[X|Y]$

LLSE problems:  $\hat{X}(Y) = a + bY$  with same goal as before but  $\hat{X}(Y) = a + bY$ . Then use  $b = \frac{\text{cov}(X, Y)}{\text{var}(Y)}$   $a = E[X] - bE[Y]$

# HW problems:

(1)  $X_n \sim \text{Bernoulli}(t_n)$

(a) 0 in prob

$$P(X_n=0) = P(X_n=1) = \frac{1}{n} \rightarrow 0$$

(b) we have LHS TFF 3 n < 0  
where part it all  $X_{n+1} = 0$

$$\begin{aligned} (c) P(\lim_{n \rightarrow \infty} X_n = 0) &\leq \sum_{n=1}^{\infty} P(X_n = 0) \xrightarrow{n \rightarrow \infty} 0 \\ &= E P\left(\bigcap_{n=1}^{\infty} \{X_n = 0\}\right) \\ &= E \prod_{n=1}^{\infty} P(X_n = 0) \\ &= E \left( \frac{1}{n} \right)^n \xrightarrow{n \rightarrow \infty} 0 \\ &= 0 \end{aligned}$$

(2) convergence in  $L^p$

$$\begin{aligned} P(|Y_n - X| \geq \varepsilon) &= P(|X_n - X|^p \geq \varepsilon^p) \\ &\leq E[|X_n - X|^p] \end{aligned}$$

$$X_n \rightarrow X \Rightarrow P(X_n - X \geq \varepsilon) \xrightarrow{\varepsilon^p} 0$$

(3) Conf. intervals Cheb. vs. Chern. vs. CLT

$$\begin{aligned} (a) \mu \in \left( \bar{X}_n - \frac{\sigma}{\sqrt{n}} \frac{1}{\sqrt{n}}, \bar{X}_n + \frac{\sigma}{\sqrt{n}} \frac{1}{\sqrt{n}} \right) \\ = P\left( |\bar{X}_n - \mu| \leq \frac{\sigma}{\sqrt{n}} \frac{1}{\sqrt{n}} \right) = 1 - P(|\bar{X}_n - \mu| > \frac{\sigma}{\sqrt{n}} \frac{1}{\sqrt{n}}) \end{aligned}$$

(7) coupon collector convergence

$$T_n = \sum_{i=1}^n Y_i \sim \text{geom}\left(\frac{n-i+1}{n}\right)$$

$$E[T_n] = \sum_{i=1}^n \frac{1}{n-i+1} = n \sum_{i=1}^n \frac{1}{i} = n H_n$$

$$\text{var}(T_n) = E[\text{var}(Y_i)] \leq \frac{1}{n} \left( \frac{n-1}{n} \right)^2$$

$$\begin{aligned} (8) \text{ant: } \beta(\lambda) &= \frac{1-p^n}{p^n - p^{n-\lambda}} \\ &= 2\left(\frac{p}{1-p}\right)^n e^{-n\lambda} \end{aligned}$$

(9) when Markov given  $a$ ?

$$(b) P(M \in \bar{X}_n \pm \frac{1}{\sqrt{n}} \sqrt{2 \ln \frac{2}{\alpha}}) = \frac{1-\alpha}{P(1 \leq \varepsilon)} \\ = 1 - P(|\varepsilon|) \\ \geq 1 - 2e^{-h \frac{1}{2\sqrt{n}}} \\ = 1 - \frac{1}{\sigma_n^2(\varepsilon)} \end{math>$$

$$(c) P(2 \geq \varepsilon) = P(e^{t\varepsilon} \geq e^{t\varepsilon}) = \frac{E[e^{t\varepsilon}]}{e^{t\varepsilon}} \\ \text{then optimize over } t \\ P(2 \geq \varepsilon) \leq e^{-\frac{1}{2\varepsilon^2}} \text{ then } \frac{e^{t\varepsilon} - 1}{e^{t\varepsilon}} \geq \varepsilon^2$$

(d) set  $\varepsilon = \sqrt{2 \ln \frac{2}{\alpha}}$  from peak part

$$P(|X_n - \mu| \geq \frac{\sigma}{\sqrt{n}} \sqrt{2 \ln \frac{2}{\alpha}}) \leq \alpha$$

then expand,  $M - X_n$  in middle term  
then put back into abs val & done

(4) CLT no upgrade

(1)  $\varepsilon \geq 0$  by union bound

$$P(|\alpha X + Y - \alpha X_n - Y_n| \geq \varepsilon) \leq P(|\alpha(X - X_n)| \geq \varepsilon/2)$$

$$|\alpha(X - X_n)| \geq \frac{\varepsilon}{2}$$

$$\leq P(|X - X_n| \geq \frac{\varepsilon}{2\alpha})$$

$$(b) \sqrt{2} Z_{2n} - \frac{1}{2} = \frac{X_{n+1} + \dots + X_{2n}}{\sqrt{n}} - Z_n \text{ but then}$$

$$\text{thus } (Z_{2n-1}) \text{ is } Z$$

(6) CLT  $\Rightarrow$  WLLN

(a)  $\varepsilon \geq 0$

$$\lim_{n \rightarrow \infty} F_{X_n}(cc-\varepsilon) = F_c(cc-\varepsilon) = 0$$

$$\lim_{n \rightarrow \infty} F_{X_n}(cc+\frac{\varepsilon}{2}) = F_c(cc+\frac{\varepsilon}{2}) = 1$$

$$\lim_{n \rightarrow \infty} P(X_n < c \geq \varepsilon) = \lim_{n \rightarrow \infty} P(X_n < c - \varepsilon)$$

$$\stackrel{\text{CLT}}{\longrightarrow} P(Y_n > c - \varepsilon)$$

$$\stackrel{\text{CLT}}{\longrightarrow} \lim_{n \rightarrow \infty} F_{Y_n}(c - \varepsilon) = 1 - F_c(c - \varepsilon)$$

$$= 1 - \lim_{n \rightarrow \infty} F_{X_n}(c - \varepsilon) = 1 - F_c(c - \varepsilon)$$

$$(b) Z_n := \frac{\sqrt{n}}{\sigma} \left( \frac{1}{n} \sum_{i=1}^n (X_i - \mu) \right) \xrightarrow{\text{CLT}} N(0, 1)$$

$$\alpha_n := \frac{\varepsilon}{\sqrt{n}} \rightarrow 0 \text{ then } Y_n := \alpha_n Z_n$$

$$= \frac{1}{\sqrt{n}} \sum_{i=1}^n (X_i - \mu) \rightarrow 0 \quad c = 0 \Rightarrow Y_n$$

also  $\rightarrow 0$  in prob.