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M ST 6540 HW#1

1.2 #6

$X + Y$ r.v. is distribution for $F_x(x) F_y(y)$

a) Let $Z = \max\{X, Y\}$, Then

$$P(Z \leq z) = F_Z(z) = P(\max\{X, Y\} \leq z)$$

$$= P(X \leq z \cap Y \leq z) \quad \text{and since } X \perp Y$$

$$P(Z \leq z) = P(X \leq z) P(Y \leq z) = F_x(z) F_y(z)$$

b) Let $W = \min\{X, Y\}$

$$P(W \leq w) = P(\min\{X, Y\} \leq w) = 1 - P(\min\{X, Y\} > w).$$

$$\text{Now } P(\min\{X, Y\} > w) = P(X > w) P(Y > w) \text{ since}$$

$X \perp Y$. Remembering that $P(X > w) = 1 - F_x(w)$

we see

$$P(W \leq w) = F_W(w) = 1 - (1 - F_x(w))(1 - F_y(w))$$

1.2. P13

(random)

Let π be a permutation of $\{1, \dots, 13\}$

Let $N = \sum k : \pi(k) = k$ be the number of matches (fixed points). Let A_k be the event $\pi(k) = k$. $A_i \cap A_j = \emptyset$ if $i \neq j$ i.e. $\{A_k\}$ +

Now we can write $N = \#\{A_1\} + \dots + \#\{A_{13}\}$

Use linearity of expectation and that

$$P(A_k) = \frac{1}{13} \text{ for } k \text{ to get}$$

$$E[N] = \sum_{k=1}^{13} E[\#\{A_k\}] = \sum_{k=1}^{13} [1 \cdot P(A_k) + 0 \cdot P(A_k^c)] \\ = \sum_{k=1}^{13} \frac{1}{13} = 1.$$

Notice $P(N=k) = \frac{\text{ways to choose } k \text{ fixed points}}{\text{ways to choose } N \text{ objects}} \times \frac{\text{permutations on } N-k \text{ with no fixed points}}{\text{permutations on } N \text{ objects}}$

↑
derangements

1. 2. P13

$$X \perp Y \sim U[0, 1] \quad \text{let } U = \max\{X, Y\} \quad V = \min\{X, Y\}$$

Find joint pdf of U, V .

$$\text{First } P(U \leq u) = F_U(u) = P(\max\{X, Y\} \leq u)$$

$$= P(X \leq u \cap Y \leq u) = P(X \leq u) P(Y \leq u)$$

$$= F_X(u) F_Y(u) = u^2 \quad \text{since } F_X(x) = \int_0^x 1 dv = x \quad \text{and}$$
$$F_Y(y) = \int_0^y 1 dv.$$

$$\text{Similarly. } F_V(v) = P(V \leq v) = 1 - P(V > v)$$

$$= 1 - P(\min\{X, Y\} > v) = 1 - P(X > v) P(Y > v)$$

$$= 1 - (1 - F_X(v))(1 - F_Y(v)) = 1 - (1-v)^2$$

U, V are not \perp

Try direct approach;

$$P(V \leq v, U \leq u) = F_{V,U}(v, u) = P(U \leq u) - P(V > v, U \leq u)$$

We partitioned $\Omega = \{V > v\} \cup \{V \leq v\}$

and used law of total probability.

$$\text{Now } P(U \leq u) = P(X \leq u, Y \leq u) = F_X(u) F_Y(u) \text{ since}$$

$$X \perp Y \quad P(U \leq u) = u^2. \quad P(V > v, U \leq u) =$$

$$P(\min\{X, Y\} > v, \max\{X, Y\} \leq u) =$$

$$P(v < X \leq u \cap v < Y \leq u) = (F_X(u) - F_X(v))(F_Y(u) - F_Y(v))$$

$$= (u-v)^2 \quad \text{from our calculations above}$$

1.2. p(3) p2

$$F_{U,V}(u,v) = u^2 - (u-v)^2 = \int_{\alpha=0}^{\alpha=u} \int_{\beta=0}^{\beta=v} f_{U,V}(\alpha, \beta) d\alpha d\beta$$

differentiating both sides gives us $f_{U,V}(u,v)$

$$\frac{\partial^2}{\partial u \partial v} u^2 - (u-v)^2 = \frac{\partial^2}{\partial u \partial v} 2uv + v^2$$

$$= 2 \frac{\partial}{\partial u} 2u + 2v = 2$$

3rd edition
book has typo
here!

X-3.8

$$X \sim \text{Binom}(N, p) \quad Y \sim \text{Binom}(M, p)$$

$$\text{let } Z = X + Y$$

N

Then since $X = \sum_{i=1}^N B_i$ $B_i \sim \text{Bernoulli}(p)$ and

$Y = \sum_{i=1}^M B_i$ we see that

$$Z = \sum_{i=1}^M B_i + \sum_{i=1}^N B_i = \sum_{j=1}^{M+N} B_j \sim \text{Binomial}(M+N, p)$$

$$\text{Now } f_X(n) = \binom{N}{n} p^n (1-p)^{N-n} \quad f_Y(m) = \binom{M}{m} p^m (1-p)^{M-m}$$

$$\text{and } f_Z(k) = \sum_{i=-\infty}^{\infty} f_X(k-i) f_Y(i) = \sum_{i=0}^{\infty} f_X(k-i) f_Y(i)$$

where we used the fact that $X, Y \geq 0$ in the limits. Now

$$f_Z(z) = \sum_{i=0}^z \binom{N}{i} p^i (1-p)^{N-i} \binom{M}{z-i} p^{z-i} (1-p)^{M-(z-i)}$$

$$= \sum_{i=0}^z \binom{N}{i} \binom{M}{z-i} p^z (1-p)^{M+N-z}$$

We can stop here because $p^z (1-p)^{M+N-z}$ is the kernel of a Binomial $(M+N, p)$ r.v.

Fun fact $\binom{N}{i} \binom{M}{z-i}$ is kernel of hypergeometric r.v. and we can conclude $\sum_{i=0}^z \binom{N}{i} \binom{M}{z-i} = \binom{N+M}{z}$

1.3. PII

$$X+Y \sim \text{Geom}(\pi) \quad U = \min\{X, Y\} \quad V = \max\{X, Y\}$$
$$W = V - U$$

$$f_{U,W}(u,w) = P(U=u, W=w) = P(\min\{X, Y\}=u, W=w)$$

$$\text{Now look at events } A = \{X=u, Y>u, W=w\}$$

$$B = \{Y=u, X>u, W=w\} \text{ and our edge case}$$

$$C = \{X=u, Y=u, W=0\}$$

$$A = \{X=u, Y>u, W=w\} = \{X=u, Y=w+u\}$$

$$B = \{Y=u, X>u, W=w\} = \{Y=u, X=w+u\}$$

Since $X \perp Y$ and $A \cap B = \emptyset$ for $w \neq 0$

$$f_{U,W}(u,w) = P(\min\{X, Y\}=u, W=w) =$$

$$P(A) + P(B) = P(\{X=u, Y=w+u\}) + P(\{Y=u, X=w+u\})$$

$$= P(X=u) P(Y=w+u) + P(Y=u) P(X=w+u)$$

$$= p^u (1-p) p^{w+u} (1-p) + p^u (1-p) p^{w+u} (1-p)$$

$$= 2 p^u (1-p)^2 p^{w+u}$$

$$f_{U,W}(u,0) = P(C) = P(X=u, Y=u, W=0) = P(X=u, Y=u)$$

$$= P(X=u) P(Y=u) = p^u (1-p) p^u (1-p)$$

Now we can get $f_U(u)$ by summing or direct calculation from order stats

1. 3. P¹¹ p2

$$f_U(u) = \sum_{w=0}^{\infty} f_{U,W}(u, w) = f_{U,W}(u, 0) + \sum_{w=1}^{\infty} f_{U,W}(u, w)$$

$$= p^{2u} (1-p)^2 + 2p^{2u} (1-p)^2 \left(\sum_{w=1}^{\infty} p^w - 1 \right)$$

$$= p^{2u} (1-p)^2 \left[1 + \frac{2p}{1-p} \right] = p^{2u} (1-p)(1+p)$$

$$f_W(w) = \sum_{u=0}^{\infty} f_{U,W}(u, w)$$

$$f_W(0) = \sum_{u=0}^{\infty} f_{U,W}(u, 0) = (1-p)^2 \sum_{u=0}^{\infty} p^{2u} = (1-p)^2 / (1-p^2)$$

$$f_W(w) = \sum_{u=0}^{\infty} f_{U,W}(u, w) = 2(1-p)^2 p^w \sum_{u=1}^{\infty} p^{2u}$$

$$= 2(1-p)^2 p^w \frac{1}{1-p^2}$$

$$f_{U,W}(u, 0) = f_U(u) f_W(0)$$

(xx)

Revisit !

$$f_{U,W}(u, w) = f_U(u) f_W(w)$$

1. 4. E6

$$U \sim \text{Unif}[\Sigma_0, 1]$$

a) $Y = -\ln(1-U)$ $F_Y(y) = P(Y \leq y)$

$$= P(-\ln(1-U) \leq y) = P(1-U \geq e^{-y})$$
$$= P(U \leq 1-e^{-y}) = \int_{x=1-e^{-y}}^{x=0} 1 dx = 1-e^{-y}$$
$$\Rightarrow$$

$$f_Y(y) = e^{-y} \quad \leftarrow \text{we recognize kernel of exp rr.}$$

b) $W_n = U^n$ $F_{W_n}(w) = P(W_n \leq w)$ $x=w^{1/n}$

$$= P(U^n \leq w) = P(U \leq w^{1/n}) = \int_{x=0}^{\infty} 1 dx$$
$$= w^{1/n} \Rightarrow f_{W_n}(w) = \frac{1}{n} w^{\frac{1-n}{n}}$$

Note both fn's $g(x) = x^n$ $g(x) = -\ln(1-x)$ are monotonic inc on $\Sigma_0, 1$ so change of variable formula can be applied directly.

1.4.7

$$S, T \perp \quad ST \sim \exp(\lambda) \quad \text{final}$$

$$f_R(r) \quad R = S+T$$

$$f_R(r) = \int_{\eta=0}^{\eta=r} f_S(r-\eta) f_T(\eta) d\eta \quad r \geq 0$$

$$f_T(\eta) = \lambda e^{-\lambda \eta} \quad f_S(r-\eta) = \lambda e^{-\lambda(r-\eta)}$$

$$f_R(r) = \int_0^r \lambda e^{-\lambda(r-\eta)} \lambda e^{-\lambda \eta} d\eta$$

$$= \lambda^2 e^{-\lambda r} \int_0^r e^{\lambda \eta} e^{-\lambda \eta} d\eta = \lambda^2 e^{-\lambda r} r$$

which we recognize as $\Gamma(\lambda, r)$

1.5. EZ

$X = \#$ draws to select given chip \bar{c} out replacement

$$X \in \{1, 2, 3, 4\}$$

$$E[X] = \sum_{i=1}^4 P(X \geq i)$$

$$P(X \geq 1) = P(\{X > 1\} \cup \{X = 1\}) = (1 - 1/4) + 1/4 = 1 \quad (\text{makes sense})$$

$$\begin{aligned} P(X \geq 2) &= P(\{X > 2\} \cup \{X = 2\}) = P(\{X > 2\}) + P(X = 2) \\ &= [1 - (1 - 1/4)(1 - 1/3)] + [(1 - 1/4) \cdot 1/3] \end{aligned}$$

$$P(X = 1) = 1/4$$

$$P(X = 2) = (1 - 1/4) \cdot 1/3 = 1/4$$

$$P(X = 3) = (1 - 1/4)(1 - 1/3) \cdot 1/2 = 1/8$$

$$P(X = 4) = 1/8 \quad \text{by normalization}$$

$$\begin{aligned} E[X] &= 1 \cdot 1/4 + 2 \cdot 1/4 + 3 \cdot 1/8 + 4 \cdot 1/8 \\ &= \frac{3}{4} + \frac{3}{8} + \frac{1}{2} = 2 \cdot 1/8 \end{aligned}$$

Note I tried to use $E[X] = \sum_{i=1}^4 P(X \geq i)$

but didn't find that easier.

1.5.2

 X_1, \dots, X_n i.i.d. $\exp(\lambda)$ r.v.Find $F_Z(z)$ where $Z = \min\{X_1, \dots, X_n\}$

$$P(Z \leq z) = 1 - P(Z > z) = 1 - P(X_1 \leq z, X_2 \leq z, \dots, X_n \leq z)$$

$$P(X_1 \geq z, \dots, X_n \geq z) = \prod_{i=1}^n P(X_i \geq z) = \prod_{i=1}^n [1 - F_{X_i}(z)]$$

$$1 - F_{X_i}(z) = 1 - \int_0^z \lambda e^{-\lambda u} du = 1 - (1 - e^{-\lambda z}) = e^{-\lambda z}$$

$$\Rightarrow \prod_{i=1}^n [1 - F_{X_i}(z)] = e^{-n\lambda} \Rightarrow$$

$$F_Z(z) = 1 - e^{-n\lambda z}$$

1.5.7

 $X_i \sim \exp(\lambda_i)$ $i=1, \dots, n$ find d.f. of

$$V = \min\{X_1, \dots, X_n\}$$

Just as above

$$P(V \leq v) = 1 - P(V > v) = 1 - P(X_1 > v, X_2 > v, \dots, X_n > v)$$

$$= 1 - \prod_{i=1}^n [1 - F_{X_i}(v)]$$

$$= 1 - \prod_{i=1}^n e^{-\lambda_i v}$$

$$= 1 - e^{-(\sum \lambda_i)v}$$

2.1.1

$$M \sim \text{Binom}(N, p)$$

$$X | M \sim \text{Binom}(M, \pi)$$

$$P(X=x) = \sum_{m=0}^N P(X=x | M=m) P(M=m)$$

$$P(M=m) = \binom{N}{m} p^m (1-p)^{N-m}$$

and

$$P(X=x | M=m) = \binom{m}{x} \pi^x (1-\pi)^{m-x}$$

$$\text{Now } P(X=x | M=m) = P(X=x, M=m) / P(M=m)$$

but we can't have more successes than trials

$$\text{So } P(X=x, M=m) = 0 \text{ when } x > m$$

Finally

$$P(X=x) = \sum_{m=x}^N \binom{m}{x} \binom{N}{m} p^m (1-p)^{N-m} \pi^x (1-\pi)^{m-x}$$
$$= \frac{\pi^x}{(1-\pi)^x} \frac{(1-p)^N}{\sum_{m=x}^N \binom{m}{x} \binom{N}{m} \left(\frac{p}{1-p}\right)^m (1-\pi)^m}$$

We can follow the steps in the book to conclude

$$P(X=x) = \binom{N}{x} (\pi p)^x (1-\pi p)^{N-x} \sim \text{Binom}(N, \pi p)$$

I could not follow the last step to evaluate

$$\sum_{m=x}^N \frac{p^m}{(m-x)! (N-m)!} \left(\frac{1-\pi}{1-p}\right)^m$$

20104

$$X \sim \text{Binom}(N, p)$$

$$X|N \sim \text{Binom}(N, p)$$

$$N \sim \text{Binom}(M, q) \Rightarrow X \sim \text{Binom}(M, pq)$$

$$E[X] = Mpq \quad \text{from above.}$$

$$\text{So if } M = 20 \quad p = \frac{1}{2} \quad q = \frac{1}{4}$$

$$E[X] = 5/2$$

2.2.6

 $\{X_i\}$ i.i.d. r.v. d.f. F

$$X_N = \min \{k \geq 1 : X_k > A\}$$

$$\alpha = P(\{X_i > A\}) \quad M = E[X_N]$$

a) Consider

$$E[X_N | X_1 = x] = \begin{cases} x & x > A \\ E[X_N] & x \leq A \text{ since } X_1 \perp X_k \end{cases}$$

Then we can write

$$E[X_N] = \int_{m=0}^{m=\infty} E[X_N | X_1 = m] dF(m)$$

$$= \int_{m=0}^{m=A} E[X_N] dF(m) + \int_{m=A}^{m=\infty} m dF(m)$$

$$= E[X_N](1-\alpha) + \int_{m=A}^{m=\infty} m dF(m)$$

Since $P(X_1 \leq A) = 1 - \alpha$ and $P(X_1 \leq A) = \int_{m=A}^{m=\infty} m dF(m)$

b) Rearranging the above

$$M = \frac{1}{\alpha} \int_{m=A}^{m=\infty} m dF(m)$$

c) $X_i \sim \exp(\lambda) \Rightarrow E[X] = \lambda$

and

$$M = \frac{1}{\alpha} \int_{m=A}^{m=\infty} m \lambda e^{-\lambda m} dm$$

2.2.1 p2

To solve the integral note

$$\int_{u=0}^{u=\infty} u \lambda e^{-\lambda u} du = \int_{u=0}^{u=A} u \lambda e^{-\lambda u} du + \int_{u=A}^{u=\infty}$$

$$\int x e^{\alpha x} = \frac{x e^{\alpha x}}{\alpha} - \frac{e^{\alpha x}}{\alpha^2} \quad \text{using integration by parts if I recall}$$

$$\int_{u=A}^{u=\infty} (\lambda u) e^{-\lambda u} du \quad \text{set } z = \lambda u$$

$$\int_{z=A\lambda}^{z=\infty} z e^{-z} dz = z e^{-z} - e^{-z} \Big|_{z=A\lambda}^{z=\infty}$$

$$= A\lambda e^{-A\lambda} + e^{-A\lambda}$$

Putting this in $\lambda = \frac{1}{\alpha} \int_{u=A}^{u=\infty} u \lambda e^{-\lambda u} du$

$$\lambda = \frac{1}{\alpha} e^{-A\lambda} (A\lambda + 1)$$

hmm... revisit

(x)

2.3.81

$$N \sim \text{unif}(1, 2, \dots, 6) \quad z|N \sim \text{Binomial}(N, \frac{1}{2})$$

Find $E[z]$ $\text{Var}(z)$ by looking at z as

random sum

$$Z = \left\{ \sum_{i=1}^N X_i \mid X_i \sim \text{Bernoulli}\left(\frac{1}{2}\right) \right.$$

$$E[Z] = \sum_{n=1}^6 E[Z|N=n] P(n)$$

$$= \sum_{n=1}^6 E[\sum_{i=1}^n X_i | N=n] P(n)$$

$$= \sum_{n=1}^6 n E[X_i] \cdot P(n) \quad E[X_i] = \frac{1}{2}$$

$$E[Z] = \frac{1}{2} \sum_{n=1}^6 n = 21/12 = 7/4 \quad P(n) = 1/6$$

For the variance we'll follow the argument

in the book let $E[X_i] = \mu = \frac{1}{2}$ $\text{Var}(X_i) = \sigma^2 = \frac{1}{2} (1 - \frac{1}{2}) = \frac{1}{4}$ $E[N] = \nu = \frac{21}{6}$ $\text{Var}[N] = \zeta^2 = 35/12$
(abusing notation we recycle)

$$\text{Then } \text{Var}(Z) = \nu \sigma^2 + \mu^2 \zeta^2 = \frac{21}{6} \cdot \frac{1}{4} + \frac{1}{4} \cdot \frac{35}{12}$$
$$\approx 1.60416$$

To find the pmf we need the n -fold convolution of X_i

2. 3. ε1 p2

$$f_z(z) = \sum_{n=1}^6 f^{(n)}(z) P_N(n)$$

But we know $P_N(n) = \frac{1}{6}$ and that $f^{(n)}(z)$ is the Binomial $(n, 1/2)$ \therefore

$$f_z(z) = \sum_{n=1}^6 \binom{n}{z} \left(\frac{1}{2}\right)^z \left(\frac{1}{2}\right)^{n-z} \cdot \frac{1}{6}$$

and we can put in $n=1, 2, 3, 4, 5, 6$ to get the values.

x x out of time
— to compute!

of
of
first
last
z elements
q^{1st}

2.3. P1

$N \sim \text{Poisson}(\lambda)$ $Z|N \sim \text{Binomial}(N, p)$

$Z = \sum_{i=1}^N X_i \quad X_i \sim \text{Bernoulli}(p)$

$$E[Z] = \sum_{n=0}^{\infty} E[Z \mid N=n] P_N(n)$$

$$= \sum_{n=0}^{\infty} E\left[\sum_{i=1}^n X_i \mid N=n\right] P_N(n)$$

$$\text{Now } P_N(n) = \frac{\lambda^n e^{-\lambda}}{n!} \text{ and}$$

$$= E\left[\sum_{i=1}^n X_i \mid N=n\right] = n p \quad \Rightarrow$$

$$E[Z] = \sum_{n=0}^{\infty} n p \frac{\lambda^n e^{-\lambda}}{n!} = p \sum_{n=0}^{\infty} n \frac{\lambda^n e^{-\lambda}}{n!}$$

$$= p E[\exp(\lambda)] - p \lambda$$

We will use book for var

$$\text{Var}(Z) = E[N] \text{Var}(X_i) + E[X_i]^2 \text{Var}(Z)$$

$$= \lambda p(1-p) + p^2 \lambda = \lambda p$$

bet $Z \sim \text{Poisson}(\lambda p)$

$$2 \cdot 3 \cdot p^2$$

$Z \sim \text{Binomial}(N, p)$ $N \sim \text{Binomial}(M, q)$

$$Z = \sum_{i=1}^N X_i$$

$$P_Z(z) = \left\{ \begin{array}{ll} P_N(0) & N=0 \end{array} \right.$$

$$f_Z(z) = \left\{ \begin{array}{ll} \sum_{n=1}^M f^{(n)}(z) P_N(n) & \\ & X_i \end{array} \right.$$

We know the form of $f^{(n)}(z)$ as
 $\text{Binomial}(n, p)$

$$P(Z=z) = \sum_{n=2}^M \binom{n}{z} p^z (1-p)^{n-z} \binom{M}{n} q^n ((1-q))^n$$

so like before
again no time to sort out
simplifying this. I promise to reas-

2.3. c)

$$\xi_i \text{ and } \mathbb{E}[\xi_i] = \mu \quad \text{Var}(\xi_i) = \sigma^2$$

$$S_N = \sum_{n=1}^N \xi_i$$

$$\mathbb{E}[S_N] = \mathbb{E}[\xi_i] \mathbb{E}[N]$$

$$\text{Var}(S_N) = \mathbb{E}[N] \text{Var}(\xi_i) + [\mathbb{E}[\xi_i]]^2 \text{Var}(N)$$

$$\text{If } N \sim \text{Pois}(\lambda)$$

$$\mathbb{E}[S_N] = \mu \lambda, \quad \text{Var}[S_N] = \lambda \sigma^2 + \mu^2 \lambda$$

$$\text{If } N \sim \text{Geom}(p)$$

$$\mathbb{E}[S_N] = \mu \frac{1-p}{p} \quad \text{Var}[S_N] = \frac{(1-p)\sigma^2}{p} + \mu^2 \frac{1-p}{p^2}$$

$$= \mu \frac{\lambda}{p} = \lambda \sigma^2 + \mu^2 \frac{\lambda}{p}$$

Comparing when $\lambda \rightarrow \infty$

we see that the means stay the same but the variance in the

$N \sim \text{Geom}(p)$ case is larger