

§ 5.4 p2

(P1)

Let $N(t)$ be P.P. (P) ξ_k = lifetime of k^{th} arrival.

Let $G(t)$ be c.d.f. of ξ_i $\xi_i \perp \text{i.i.d.}$

Let $X(t)$ = # customers in store $Y(t)$ = # arrived

and departed. Then $N(t) = X(t) + Y(t)$

Consider W_k - waiting time to k^{th} arrival, then

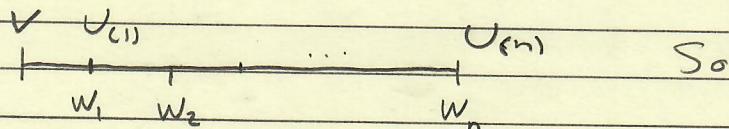
k is in store at t iff $W_k + \xi_k \geq t$. Now let

$E_k = \{ W_k + \xi_k \geq t \}$, then $P(X(t)=k | N(t)=n) = P\left(\sum_{k=1}^n E_k | N(t)=n\right)$.

Now $\{W_k\}$ jointly distributed as order stat of

$\text{Unif}[0, t]$ - conditional on n . Any sum over all

W_k can be cast as sum over the $U_k \sim \text{Unif}[0, t]$ r.v.s.



$$P(X(t)=k | N(t)=n) = P\left(\sum 1(U_k + \xi_k \geq t) = k\right)$$

rhs is $\text{Binomial}(n, p)$ with $p = P(U_k + \xi_k \geq t)$

We need the convolution thm to evaluate p

Let $Z = U + \xi$ $U \sim \text{Unif}[0, t]$ $\xi \stackrel{\text{c.d.f.}}{\sim} G$

$$F_Z(z) = \int_{-\infty}^{\infty} F_U(z-u) F_\xi(u) du \quad \text{or} \quad f_Z(z) = \int_{-\infty}^{\infty} f_U(z-u) f_\xi(u) du$$

$$= \int_{-\infty}^{\infty} \frac{z-u}{t} G(u) du$$

§ 5.4 P2

How to find joint distribution? Note

$$Y(t) = j, X(t) = k \Rightarrow N(t) = j+k . \text{ Now write}$$

$$P(X(t) = k, Y(t) = j) = P(X(t) = k, N(t) = j+k) =$$

$$P(X(t) = k | N(t) = j+k) P(N(t) = j+k)$$

$$\frac{(j+k)!}{(k)! (j)!} p^k (1-p)^j \frac{(at)^{j+k}}{(j+k)!} e^{-\lambda t}$$

Ex

More about $P(U_k + \xi_k \geq t)$. First $P(U \leq z)$

$$= F_U(z) = \int_{u=0}^{u=t} \frac{1}{t} du, \quad P(U > z) = 1 - F_U(z)$$

In our convolution formula there are two ways to

$$\text{convolve } F_{U+\xi}(z) = \int_{u=-\infty}^{u=\infty} F_U(z-u) F_\xi(u) du$$

$$= \int_{u=-\infty}^{u=\infty} F_U(u) F_\xi(z-u) du . \quad \text{Using the second form}$$

and noting $F_U(u) = 0 \quad u < 0$ we have

$$P(U + \xi = z) = \int_0^\infty \frac{1}{t} G(z-u) du . \quad \text{Close } \circ \circ$$

1 S. 4. P1 w_1, \dots, w_n arrivals $PP(\pi)$

2
3 $X(1) = n$ $k < n$ Find density of

4
5 $w_1, w_2, \dots, w_{k-1}, w_{k+1}, \dots, w_n \mid w_k = w, X(1) = n$

6
7 We note our $U_{(i)} \sim U[0, 1]$

8
9 The order stats of k^{th} o.s. $U_{(k)}$

10
11 $f_{U_{(k)}}(u) = \frac{u!}{(k-1)!(n-k)!} u^{k-1} (1-u)^{n-k}$

12
13 $U_{(k)} \sim \text{Beta}(k, n+1-k)$

14
15 We can make prob arg

16
17 $f_{w_1, \dots, w_n \mid X(1)=n}(w_1, \dots, w_n) = n!$

18
19 How can we have $k-1$ to left of $U_{(k)}$

20
21 $n-k+1$ to right of $U_{(k)}$ given that $U_{(k)} = w$?

22
23 We can also write $f_{w_1, \dots, w_{k-1}, w_{k+1}, \dots, w_n \mid X(1)=n, w_k=w}$

24
25 $= f_{w_1, \dots, w_n \mid X(1)=n} / f_{w_k} = \frac{n!}{\frac{w_1 \dots w_n}{(k-1)!(n-k)!} u^{k-1} (1-u)^{n-k}}$

5.4. P1

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$$f_{W_1, \dots, W_{k-1}, W_k, \dots, W_n} | X(1)=n, W_k = w = \frac{n!}{\frac{n!}{(k-1)!} w^{k-1} (1-w)^{n-k}}$$

5.4 P5

1 $N(t) \quad P.P.(\gamma)$ find $\lim_{n \rightarrow \infty} P(W_i=t | N(t)=n)$

2
3 $W_n \sim \Gamma(n, \gamma), \quad W_i \stackrel{\text{def}}{\sim} \Gamma(1, \gamma) = \exp(\gamma)$

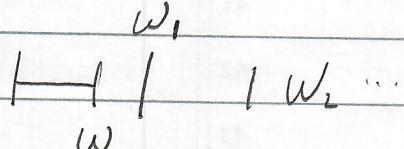
4
5 $f_{W_n}(t) = \frac{1}{\Gamma(n)} (\gamma t)^{n-1} e^{-\gamma t}$

6
7 We know $f_{W_i, W_{n-1}, \dots, W_1}(t) = n! t^{n-1}$

8
9 Do we marginalize over W_n, W_{n-1}, \dots, W_1

10 - remembering $W_1 < W_2 < \dots < W_n$

11
12 $P(W_1 > w | N(t)=n)$



13
14 $\Rightarrow \{W_i > w\} \Rightarrow$ all waiting times to

15 the right of w . - same as prob of

16
17 all $U_{(i)} > w \quad U_k \perp \Rightarrow$

18
19 $P(W_1 > w | N(t)=n) = P(U_1 > w, U_2 > w, \dots, U_n > w)$

20
21 $= \prod_{i=1}^n P(U_i > w) = \left(1 - \frac{w}{t}\right)^n$

22
23 Now let $\frac{n}{t} = \beta$ and take limit

24
25 $\lim_{n \rightarrow \infty} \left(1 - \frac{\beta w}{n}\right)^n = e^{-\beta w}$

1 S.Y PS

⑦

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$$\lim_{n \rightarrow \infty}^3 P(W_1 > w | N(t) = n) = 1 - F_{W_1|N}(w) = e^{-\beta w}$$

5

$$F_{W_1|N}(w) = 1 - e^{-\beta w}$$

6

$$\frac{d}{dw} F_{W_1|N}(w) = \beta e^{-\beta w} \Rightarrow$$

7

$$W_1|N = \exp(\beta). \text{ My notation is bad.}$$

8

What really happens to N when we take

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limit? $W_1|N$ becomes something

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that does not depend on N .

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1 5. 6. 84

2 $X(t)$ P.P.(2) $Y(t)$ P.P.(4)

3 Treat Y as a marking for X

4 (X, Y) ? Then the sojourn times

5 of X determine Y , which violates conditions

6 of a marked P.P. What if we

7 combine X, Y to make one P.P.(2+4)

8 and then mark each arrival of $Z = X + Y$

9 accordingly? Let G be discrete rv.

10 $P(G = \text{male}) = 1/3$ $P(G = \text{female}) = 2/3$, then

11 (Z, G) should provide the answers

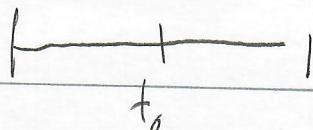
12 were looking for. Each customer enters

13 at a rate of 6, and is independently

14 male \in prob $p = 1/3$ and female \in prob $1 - 1/3$

part b)

couple not figure out



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Let t_0 be an arbitrary time, and

T be the time 2 men arrive

$$P(Y(T-t_0) = 0, X(T-t_0) = 2) \quad \text{let } s = T-t_0$$

then $P(Y(s) = 0, X(s) = 2)$ is what we're

looking for. Due to the independence of

Y, X - BUT WHAT IS s ? It's a RV,

$$P(Y(s) = 0 | X(s) = 2) = P(Y(s) = 0, X(s) = 2) / P(X(s) = 2)$$

$$P(X(s) \geq 2, Y(s) \leq 2)$$

What is s ?

$$Z = X + Y \quad \text{if } X=2$$

Is it this easy?

XX

$$P(\text{mate, mate}) = \frac{1}{3} \cdot \frac{1}{3} = \frac{1}{9}$$

$$\frac{6}{9} \frac{6}{9}$$

$$\begin{array}{c|cc} & F & F \\ \hline M M F F & & \\ M F M F & & \end{array}$$

$$6 \left(\frac{1}{3}\right)^2 \left(\frac{2}{3}\right)^2 = \frac{24}{81} = \frac{8}{27}$$

$$8 + 8 = 16$$

1 $N(t)$

2 $X(t) = \sum_{i=1}^N Y_i$ $Y_i \sim \text{Geom}(p)$

5 Then following the book - if T
 6

7 is random failure time, we have
 8

9 $\{T > t\} \text{ iff } \{X(t) < a\}$

11 Using S.34 with $P(X(t))$ and $a = \infty$ we have

13 $P(X(t) < a) = \sum_{n=0}^{\infty} \frac{(\lambda t)^n e^{-\lambda t}}{n!} G^{(n)}(a)$

15 $= P(T > t) \Rightarrow$

16 $E[T] = \int_{t=0}^{t=\infty} P(T > t) dt = \int_{t=0}^{t=\infty} \sum_{n=0}^{\infty} \frac{(\lambda t)^n}{n!} e^{-\lambda t} G^{(n)}(a) dt$

19 $= \sum_{n=0}^{\infty} \int_{t=0}^{t=\infty} \frac{(\lambda t)^n}{n!} e^{-\lambda t} dt G(a) dt$

22

23 The integral can be evaluated noting
 24

25 we have Gamma($n+1, \lambda$) kernel.
 26

27 $E[T] = \sum_{n=0}^{\infty} n G^{(n)}(a)$

1 5.6 p3

(2)

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3 I Looked up the n-fold convolution

4

5 or $\text{Geom}(p)$; $Y_i \text{ iid } \text{Geom}(p) \Rightarrow$

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7 $\sum_{i=1}^n Y_i \sim \text{Negative Binomial}(n, p)$

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9
10 IF I recall - there's a nice argument11
12 why this is the case. We should also13
14 be able to verify directly with convolution15
16 Formula. - revisit both of these.

17

18
19 We still need to calculate $G^{(n)}(a)$ & f_n 20
21 $G^{(n)}(a) = \text{cdf } NB(n, p)$ which I22
23 looked up - It's a regularized incomplete24
25 β -fn. This is looking more complex26
27 than might be necessary.

28

5.6 P3

(3)

Instead of using cdf we note

$$G(a) = P(N.B.(n, p) \leq a)$$

$$= \sum_{i=1}^a \xi_i \quad \text{where } \xi_i = \binom{i+n-1}{i} (1-p)^i p^n$$

are the $N.B(n, p)$ probabilities.

$$\text{Now } E[\xi_i] = \frac{1}{\lambda} \sum_{n=0}^{\infty} \sum_{i=0}^a \binom{i+n-1}{i} (1-p)^i p^n$$

Hopefully exchanging sums will simplify

$$E[\xi_i] = \frac{1}{\lambda} \sum_{i=0}^a \sum_{n=0}^{\infty} \frac{(i+n-1)!}{i! (n-1)!} (1-p)^i p^n$$

$$= \frac{1}{\lambda} \sum_{i=0}^a \frac{(1-p)^i}{(i!)^2} \sum_{n=0}^{\infty} \frac{(i+n-1)!}{\overbrace{(n-1)!}^{(i-1)!}} p^n$$

1 Extra HW

2
3 $X(t)$ P.P. (λ) each arrival type 1 or prob p

4
5 type 2 \in prob $1-p$ \perp arrivals.

6
7 $X_1(t) = \# \text{type 1} \in [0, t]$ $X_2(t) = \# \text{type 2} \in [0, t]$

8
9 Prove $X_1(t)$ P.P. ($p\lambda$) $X_2(t)$ P.P. ($(1-p)\lambda$)

10
11 and $X_1 \perp X_2$

12
13 What do we need to show? ① $X_1(0) = X_2(0) = 0$

14
15 ② \perp increments poisson distributed.

16
17 ① is easy $X_1(t) + X_2(t) = X(t) + X(0) = 0$

18
19 $X_1(t) X_2(t) \geq 0 \Rightarrow X_1(0) = X_2(0) = 0$.

20
21 For ② we will use conditioning and LTP.

22
23 in the form of Thm 3.2

24
25 $X|N \sim \text{Binom}(N, p)$ $N \sim \text{Pois}(\lambda) \Rightarrow$

26
27 $X \sim \text{Pois}(p\lambda)$

1 Extra H.W.

(2)

3 First establish $X_1 | N \sim \text{Binom}(N, p)$

5 $P(X_1(t) = m | X(t) = n)$ is the probability

7 of m Bernoulli successes in n trials.

9 For now on $N = X$ - so

11 $X_1 | X \sim \text{Binom}(X, p)$ and since

13 $X(t) \sim \text{Pois}(\lambda t)$ we have our result

15 $X_1(t) \sim \text{Pois}(p\lambda t)$. Applying similar

17 argument to X_2 $X_2(t) \sim \text{Pois}((1-p)\lambda t)$

19 Now we need to establish $X_1(t) + X_2(t)$

21 This should follow trivially by the

23 independence of our labeling as type 1, type 2.

25 I tried to show $P(X_1(t) = m, X_2(t) = n) = P(X_1(t) = m) P(X_2(t) = n)$

27 (revise) $P(X_1(t) = m, X_2(t) = n) = P(X_1(t) = m | X_2(t) = n) P(X_2(t) = n)$

28 $P(X_1(t) = m | X_2(t) = n) = P(X_1(t) = m | X(t) = n+m) \sim \text{Binom}(x^t)$