

Another Conditional expectation example

Stat 527

3-2-17

Binomial

(1)

$$p_{X|p}(x|p) = \binom{n}{x} p^x q^{n-x}, \text{ where } p \sim \text{Unif}(0,1) \text{ (prior distribution)}$$

Goal: find $E[p|X=x]$ (Bayesian estimate of p , \hat{p} , using squared-error loss)

Joint distribution of X, p

$$f(x, p) = p_{X|p}(x|p) \cdot \underbrace{f_p(p)}_1 = \binom{n}{x} p^x q^{n-x}$$

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$$p_X(x) = \int_0^1 f(x, p) dp$$

$$= \int_0^1 \binom{n}{x} p^x q^{n-x} dp$$

$$= \binom{n}{x} \underbrace{\int_0^1 p^x q^{n-x} dp}$$

$$= \binom{n}{x} \frac{\Gamma(x+1)\Gamma(n-x)}{\Gamma(n+2)} \underbrace{\int_0^1 \frac{\Gamma(n+2)}{\Gamma(x+1)\Gamma(n-x+1)} p^x q^{n-x} dp}$$

Beta distribution with

$$\alpha = x+1, \beta = n-x+1$$

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$$= \frac{n!}{\cancel{x!} \cancel{(n-x)!}} \frac{\cancel{x!} \cancel{(n-x)!}}{(n+1)!}$$

$$P_X(x) = \frac{1}{n+1} \quad x = 0, 1, \dots, n$$

Note: Each of the $n+1$ values that

X can take on is equally likely

[X has a "discrete uniform" distribution]

$$f_{p|X}(p|x) = \frac{f(p,x)}{P_X(x)} = \frac{\binom{n}{x} p^x q^{n-x}}{1/(n+1)}$$

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$$f_{p|X}(p|x) = (n+1) \binom{n}{x} p^x q^{n-x}, \quad x = 0, 1, \dots, n, \\ \text{(posterior distribution of } p) \quad 0 < p < 1$$

$$E[p|X=x] = \int_0^1 p(n+1) \binom{n}{x} p^x q^{n-x} dp$$

$$= (n+1) \binom{n}{x} \int_0^1 p^{x+1} q^{n-x} dp$$

$$= (n+1) \binom{n}{x} \frac{\Gamma(x+2) \Gamma(n-x+1)}{\Gamma(n+3)} \underbrace{\int_0^1 \frac{\Gamma(n+3)}{\Gamma(x+2) \Gamma(n-x+1)} p^{x+1} q^{n-x} dp}_1$$

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$$= \frac{(n+1) n!}{x! (n-x)!} \frac{(x+1)! (n-x)!}{(n+2)!}$$

$$E[p|x=2] = \frac{x+1}{n+2}$$

Note: this lies between

$\frac{x}{n}$, which would be \hat{p} in

a non-Bayesian setting,

and $\frac{1}{2}$, which is the mean

of the prior distribution.

The Compounding Identity

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Theorem: X_1, X_2, \dots i.i.d

N independent of the X_i 's, non neg. integer

$$S_N = \sum_{i=1}^N X_i, \quad h(S_N) \text{ is any function of } S_N.$$

$$\text{Then } E[S_N h(S_N)] = E[N] E[X_1 h(S_N)],$$

where M is a new random variable such that $P(M=n) = \frac{n P(N=n)}{E[N]}$.

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Proof: $E[S_N h(S_N)] = E\left[\sum_{i=1}^N X_i h(S_N)\right]$

$$= E\left(E\left[\sum_{i=1}^N X_i h(S_N) \mid N\right]\right)$$

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

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

$$= \sum_{n=0}^{\infty} \sum_{i=1}^n E[X_i h(S_n)] P[N=n]$$

$$= \sum_{n=0}^{\infty} n E[X_1 h(S_n)] P[N=n]$$

$$= E[N] \sum_{n=0}^{\infty} E[X_1 h(S_n)] \frac{n P[N=n]}{E[N]}$$

$$= E[N] \sum_{n=0}^{\infty} E[X_1 h(S_n)] P[M=n]$$

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$$= E[N] \sum_{n=0}^{\infty} E[X_1 h(S_n) | M=n] P[M=n]$$

↑
OK since M is
indep. of X_1, \dots, X_n

$$= E[N] \sum_{n=0}^{\infty} E[X_1 h(S_n) | M=n] P[M=n]$$

$$= E[N] E[E[X_1 h(S_n) | M]]$$

$$= E[N] E[X_1 h(S_n)]$$

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Corollary: $P[S_N = 0] = P[N = 0]$ and

$$P[S_N = k] = \frac{1}{k} E[N] \sum_{j=1}^k j \alpha_j P[S_{N-1} = k-j],$$

$k > 0$ and $\alpha_j = P[X_1 = j]$ and

X_1, \dots, X_n, \dots are integer-valued > 0

Proof. Fix a value of k .

$$\text{Let } h(S_N) = \begin{cases} 1 & \text{if } S_N = k \\ 0 & \text{otherwise} \end{cases}$$

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$$\text{Now } S_N h(S_N) = \begin{cases} k & \text{if } S_N = k \\ 0 & \text{otherwise} \end{cases}$$

$$\text{And } E[S_N h(S_N)] = k P[S_N = k]$$

So the theorem says

$$\begin{aligned} k P[S_N = k] &= E[N] E[X_1 h(S_N)] \\ &= E[N] E[E[X_1 h(S_N) | X_1]] \\ &= E[N] \sum_{j=1}^k E[X_1 h(S_N) | X_1 = j] P[X_1 = j] \end{aligned}$$

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$$\begin{aligned} &= E[N] \sum_{j=1}^k j E[h(S_N) | X_1 = j] \alpha_j \\ &= E[N] \sum_{j=1}^k j \underbrace{P[S_N = k | X_1 = j]} \alpha_j \end{aligned}$$

$$\begin{aligned} P[S_N = k | X_1 = j] &= P\left[\sum_{i=1}^N X_i = k | X_1 = j\right] \\ &= P\left[j + \sum_{i=2}^N X_i = k\right] \end{aligned}$$

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$$= P\left[\sum_{i=2}^M X_i = k-j\right]$$

$$= P\left[\sum_{i=1}^{M-1} X_i = k-j\right]$$

$$= P[S_{M-1} = k-j]$$

$$\therefore k P[S_n = k] = E[W] \sum_{j=1}^k j \alpha_j P[S_{n-1} = k-j]$$