

## lecture 28

Last time:

Prop: Suppose that  $X_i \sim N(\mu_i, \sigma_i^2)$  a normal RV. Then  $\sum_i X_i \sim N(\sum \mu_i, \sum \sigma_i^2)$ .

Recall that  $Y$  is called lognormal<sup>with parameters  $\mu, \sigma$</sup>  if  $Y = e^X$  for  $X \sim N(\mu, \sigma^2)$ .

Ex: Suppose that  $S(n)$  is the price of a certain security at the end of  $n$  weeks from right now. A popular model for the evolution of these prices assumes that the price ratios  $S(n)/S(n-1)$ ,  $n \geq 1$ .



Assuming the model has parameters  $\mu = 0.0165$  and  $\sigma = 0.0730$ , what is the prob that the price of the security at the end of two weeks is higher than it is today?

Solution: Observe that  $S(2) > \underbrace{S(0)}_{\text{price r.n.}}$   
iff  $\frac{S(2)}{S(0)} > 1$ .

$$\begin{aligned} \text{So we want } P\left(\frac{S(2)}{S(0)} > 1\right) &= P\left(\frac{S(2)}{S(1)} \cdot \frac{S(1)}{S(0)} > 1\right) \\ &= P\left(\log\left(\frac{S(2)}{S(1)}\right) + \log\left(\frac{S(1)}{S(0)}\right) > 0\right). \end{aligned}$$

$$\text{Now, } \log\left(\frac{S(n)}{S(n-1)}\right) = N(0.065, (0.0730)^2)$$

$$\text{So } \log\left(\frac{S(2)}{S(1)}\right) + \log\left(\frac{S(1)}{S(0)}\right) = N\left(\underbrace{2(0.065)}_{0.130}, 2(0.0730)^2\right)$$

$$\text{Hence } P\left(\frac{S(2)}{S(0)} > 1\right) = P\left(N(0.130, 2(0.0730)^2) > 0\right)$$

$$= P\left(Z > \frac{-0.0370}{(0.0730)\sqrt{2}}\right) = 0.6254.$$

Some Examples of Sums of independent RV's in  
the Discrete Case

Ex: Sums of independent Poisson RV's.

Recall that  $X$  is Poisson with parameter  $\lambda$

if  $X$  has a probability mass function given

$$\text{by } P_X(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

Suppose that  $X_1$  and  $X_2$  are independent Poisson RV's with parameters  $\lambda_1, \lambda_2$  respectively.

Then, for any  $n$ ,

$$\begin{aligned} P_{X_1+X_2}(n) &= P(X_1+X_2=n) = \sum_{k=0}^n P(X_1=k, X_2=n-k) \\ &= \sum_{k=0}^n P(X_1=k) P(X_2=n-k) \leftarrow \text{by indep.} \\ &= \sum_{k=0}^n \left( \frac{e^{-\lambda_1} \lambda_1^k}{k!} \right) \left( \frac{e^{-\lambda_2} \lambda_2^{n-k}}{(n-k)!} \right) \end{aligned}$$

$$\begin{aligned}
 &= e^{-(\lambda_1 + \lambda_2)} \sum_{k=0}^n \frac{\lambda_1^k \lambda_2^{n-k}}{k! (n-k)!} \quad \text{multiply by } \frac{n!}{n!} = 1. \\
 &= \frac{e^{-(\lambda_1 + \lambda_2)}}{n!} \sum_{k=0}^n \frac{n!}{k! (n-k)!} \lambda_1^k \lambda_2^{n-k} \\
 &= \frac{e^{-(\lambda_1 + \lambda_2)}}{n!} \sum_{k=0}^n \binom{n}{k} \lambda_1^k \lambda_2^{n-k} \quad \text{Binomial theorem.} \\
 &= \frac{e^{-(\lambda_1 + \lambda_2)}}{n!} (\lambda_1 + \lambda_2)^n
 \end{aligned}$$

Hence  $X_1 + X_2$  is again a Poisson RV with parameter  $\lambda_1 + \lambda_2$ .

By induction on the # of RV's, if  $X_1, \dots, X_m$  are independent Poisson RV's with parameters  $\lambda_i$ ,  $i=1, \dots, m$ . Then  $\sum_{i=1}^m X_i$  is again a Poisson RV with parameter  $\sum_{i=1}^m \lambda_i$ .

Ex: Sums of binomial RV's with fixed  $p$ .

Suppose that  $X = \text{Bin}(n, p)$   $Y = \text{Bin}(m, p)$ .

By definition  $X$  and  $Y$  are sums of independent Bernoulli trials. By independence,  $X + Y = \text{Bin}(n+m, p)$ . (See the text for a formal proof).

## Conditional Distributions

### Discrete Case:

Recall that for events  $E$  and  $F$ ,

$$P(E|F) = \frac{P(EF)}{P(F)}, \text{ if } P(F) > 0.$$

Suppose that  $X$  and  $Y$  are discrete RV's.

Defn: The conditional pmf of  $X$  given  $Y=y$  is defined

$$\begin{aligned} P_{X|Y}(x|y) &= P(X=x|Y=y) \\ &= \frac{P(X=x, Y=y)}{P(Y=y)} = \boxed{\frac{p(x,y)}{p_y(y)}} \end{aligned}$$

for all  $y$  s.t.  $p_y(y) > 0$ . (Here,  $p(x,y)$  is the joint prob mass function and  $p_y(y)$  is the marginal probability of  $Y$ .)

We can derive an expression for the "cumulative conditional probability of  $X$  given  $Y=y$ " as

$$\begin{aligned} F_{X|Y}(x|y) &= P(X \leq x|Y=y) \\ &= \sum_{a \leq x} P_{X|Y}(a|y) \end{aligned}$$

(Note that these definitions are symmetric in  $X$  and  $Y$ ).

Observation: If  $X$  and  $Y$  are independent, then

$$\begin{aligned} P_{X|Y}(x|y) &= \frac{P(X=x, Y=y)}{P(Y=y)} = \frac{P(X=x)P(Y=y)}{P(Y=y)} \\ &= P(X=x) = P_X(x). \end{aligned}$$

Ex: Let  $X_1, X_2$  be <sup>independent</sup> Poisson RV's with parameters  $\lambda_1, \lambda_2$  resp. Find the conditional distribution of  $X_1$  given that  $X_1 + X_2 = n$ .

$$\begin{aligned} \text{Soln: } P_{X_1|X_1+X_2}(k|n) &= P(X_1=k | X_1+X_2=n) \\ &= \frac{P(X_1=k, X_1+X_2=n)}{P(X_1+X_2=n)} \\ &= \frac{P(X_1=k, X_2=n-k)}{P(X_1+X_2=n)} \\ &= \frac{P(X_1=k) P(X_2=n-k)}{P(X_1+X_2=n)} \quad \left( \text{by indep. of } X_1, X_2 \right). \end{aligned}$$

Now, furthermore,  $X_1 + X_2$  is Poisson with parameter  $\lambda_1 + \lambda_2$ , so

$$\begin{aligned} P_{X_1|X_1+X_2}(k|n) &= \frac{\left(\frac{e^{-\lambda_1} \lambda_1^k}{k!}\right) \left(\frac{e^{-\lambda_2} \lambda_2^{n-k}}{(n-k)!}\right) \left(\frac{n!}{e^{-(\lambda_1+\lambda_2)} (\lambda_1+\lambda_2)^n}\right)}{k! (n-k)!} \\ &= \frac{n!}{k! (n-k)!} \frac{\lambda_1^k \lambda_2^{n-k}}{(\lambda_1 + \lambda_2)^n} \\ &= \binom{n}{k} \left(\frac{\lambda_1}{\lambda_1 + \lambda_2}\right)^k \left(\frac{\lambda_2}{\lambda_1 + \lambda_2}\right)^{n-k} \end{aligned}$$

Now, observe that

$$1 - \frac{\pi_1}{\pi_1 + \pi_2} = \frac{(\pi_1 + \pi_2) - \pi_1}{\pi_1 + \pi_2} = \frac{\pi_2}{\pi_1 + \pi_2} \quad (> 1)$$

and so

$$P_{X_1|X_1+X_2}(k|n) = \binom{n}{k} p^k (1-p)^{n-k}, \text{ where } p = \frac{\pi_1}{\pi_1 + \pi_2}.$$

binomial

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Next: Conditional distributions, the continuous case:

Suppose that  $X$  and  $Y$  are jointly distributed with density  $f(x, y)$ . Then we define the conditional probability of  $X$  given  $Y$  as

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}, \quad f_Y(y) > 0.$$