

+ characteristic functions
Random variable X which takes values
in state space $S = \mathbb{Z}_{20}$.

Probability generating function

$$G_X(s) = \langle s^X \rangle \quad \text{defined for } \mathbb{R} \text{ s.t. } -1 \leq s \leq 1.$$

Characteristic function

$$\phi_X(k) = \langle e^{ikX} \rangle \quad \text{defined for all real } k.$$

- this is also the "moment generating fn"

Cumulant generating fn

$$\hat{\phi}_X(k) = \ln \phi_X(k)$$

Application: Suppose I have a random variable

$$Z = \sum_{j=1}^N X_j$$

where N is random, Poisson distributed,
with $\langle N \rangle = \lambda$.

and the $\{X_j\}$ are i.i.d. with

$$\text{Prob}(X_j = 1) = p$$

$$\text{Prob}(X_j = 0) = 1 - p$$

N is independent of the $\{X_j\}$

Direct Question: What is the prob. dist. for
 Z ?

Direct calculation:

$$\text{Prob}(N = n) = e^{-\lambda} \frac{\lambda^n}{n!} \quad \text{because } \langle N \rangle = \lambda.$$

for $n \in \mathbb{Z}_{\geq 0}$.

$$\text{Prob}(Z = k) = \sum_{n=0}^{\infty} \text{Prob}(Z = k \text{ and } N = n)$$

(rule of marginal probability)

$$= \sum_{n=0}^{\infty} \text{Prob}(Z = k | N = n) \text{Prob}(N = n)$$

(rule of conditional probability)

$$\text{Prob}(A \text{ and } B) = \text{Prob}(A|B) \text{Prob}(B)$$

$$\text{Prob}(Z = k | N = n)$$

$$Z = \sum_{j=1}^n X_j$$

$$= \binom{n}{k} p^k (1-p)^{n-k}$$

for $0 \leq k \leq n$

$$= 0 \text{ for } k > n$$

$$\text{Prob}(Z = k) = \sum_{n=k}^{\infty} \binom{n}{k} p^k (1-p)^{n-k} \frac{e^{-\lambda} \lambda^n}{n!}$$

$$= \sum_{n=k}^{\infty} \frac{n!}{(n-k)! k!} p^k (1-p)^{n-k} \frac{e^{-\lambda} \lambda^n}{n!}$$

$$= \frac{p^k e^{-\lambda} \lambda^k}{k!} \sum_{n=k}^{\infty} \frac{(1-p)^{n-k} \lambda^{n-k}}{(n-k)!}$$

$$= \frac{p^k e^{-\lambda} \lambda^k}{k!} \sum_{m=0}^{\infty} \frac{(\lambda(1-p))^m}{m!}$$

$$= \frac{p^k e^{-\lambda} \lambda^k}{k!} e^{\lambda(1-p)}$$

$$\text{Prob}(Z=k) = \frac{e^{-\lambda p} (\lambda p)^k}{k!}$$

Z is a Poisson r.v. with $\langle Z \rangle = \lambda p$

Now by generating functions,

- independent random vars appearing in discrete chunks,

$$G_Z(s) = \langle s^Z \rangle = \langle s^{\sum_{j=1}^N X_j} \rangle$$

$$= \langle \prod_{j=1}^N s^{X_j} \rangle$$

$$= \langle \langle \prod_{j=1}^N s^{X_j} \rangle_X \rangle_N$$

$\langle \cdot \rangle_X$: average over X vars

$\langle \cdot \rangle_N$: average over N vars,

$$= \langle \prod_{j=1}^N \langle s^{X_j} \rangle_X \rangle_N = \langle (G_X(s))^N \rangle_N$$

where $G_X(s)$ is the common ^{prob.} generating function for the $\{X_j\}$

$$G_Z(s) = G_N(G_X(s))$$

$$G_N(s) = \langle s^N \rangle \quad (\text{Karlin + Taylor Sec. 1.1})$$

$$\begin{aligned} G_X(s) = \langle s^{X_j} \rangle &= \sum_{n=0}^{\infty} \text{Prob}(X_j = n) s^n \\ &= (1-p)s^0 + ps^1 + 0s^2 + 0s^3 + \dots \\ &= 1-p + ps \end{aligned}$$

$$\begin{aligned} G_N(s) = \langle s^N \rangle &= \sum_{n=0}^{\infty} \text{Prob}(N=n) s^n \\ &= \sum_{n=0}^{\infty} e^{-\lambda} \frac{\lambda^n}{n!} s^n \\ &= e^{-\lambda} \sum_{n=0}^{\infty} \frac{(\lambda s)^n}{n!} = e^{-\lambda} e^{\lambda s} \\ &= e^{\lambda(s-1)} \end{aligned}$$

Karlin + Taylor Sec. 1 has prob. gen. fn. for various basic prob. dists.

$$G_Z(s) = e^{\lambda(1-p+ps-1)} = e^{\lambda p(s-1)}$$

which is gen. fn. for Poisson rv with mean $\langle Z \rangle = \lambda p$.

Another excursion w/ gen fns, + char fns,

Random sum:

$$Z = \sum_{j=1}^N X_j \quad \text{with } N \text{ random}$$

X_j are i.i.d.

Ques from: How is mean and variance of Z related to those of the N and X_j ?

We'll address using characteristic fn and prob. gen. fn.

Characteristic function (just because it generalizes to case of continuous X_j)

$$\phi_Z(k) = \langle e^{ikZ} \rangle = \langle e^{ik \sum_{j=1}^N X_j} \rangle$$

$$= \langle \langle e^{ik \sum_{j=1}^N X_j} \rangle_{X_j} \rangle_N$$

$$= \langle \prod_{j=1}^N \langle e^{ikX_j} \rangle_{X_j} \rangle_N \quad \text{since the } X_j \text{ are independent of each other and } N,$$

$$= \langle (\phi_X(k))^N \rangle_N \quad \text{where } \phi_X(k) = \langle e^{ikX_j} \rangle \text{ for all } j \text{ (since identical d.)}$$

$$\phi_Z(k) = G_N(\phi_X(k)) \quad \text{with } G_N(s) = \langle s^N \rangle$$

Remember that ϕ is a moment generating function

$$\phi_Z(k) = \langle e^{ikZ} \rangle$$

$$\phi_X(k) = \langle e^{ikX} \rangle$$

$$\langle Z^n \rangle = \left. \left(-i \frac{d}{dk} \right)^n \phi_Z(k) \right|_{k=0}$$

~~AAA~~

$$\langle Z \rangle = \left. \left(-i \frac{d}{dk} \right) \phi_Z(k) \right|_{k=0} = -i \phi'_X(k) G'_N(\phi_X(k)) \Big|_{k=0}$$

$$= -i \phi'_X(0) G'_N(\phi_X(0))$$

$$= -i \phi'_X(0) G'_N(1)$$

$$\langle Z^2 \rangle = \left. \left(-i \frac{d}{dk} \right)^2 \phi_Z(k) \right|_{k=0} = \left. \left(-i \phi'_X(k) \right)^2 G''_N(\phi_X(k)) \right|_{k=0}$$

$$= \left. \left(-i \phi'_X(k) \right)^2 G''_N(\phi_X(k)) \right|_{k=0}$$

~~AAA~~

$$= -(\phi'_X(0))^2 G''_N(1)$$

$$- \phi''_X(0) G'_N(1)$$

Relate derivatives of ϕ_X and G_N to moments of X and N

$$-i \phi'_X(0) = \langle X \rangle = \mu_X$$

$$- \phi''_X(0) = \langle X^2 \rangle = \sigma_X^2 + \mu_X^2$$

More mathematically,

$$\phi_Z(k) = \mathbb{E} e^{ikZ} = \mathbb{E} e^{ik \sum_{j=1}^N X_j}$$

$$= \mathbb{E} \left(\mathbb{E} \left[e^{ik \sum_{j=1}^N X_j} \mid N \right] \right)$$

$$= \mathbb{E} \left(\mathbb{E} \left(\prod_{j=1}^N e^{ik X_j} \mid N \right) \right)$$

$$= \mathbb{E} \left(\prod_{j=1}^N \mathbb{E} (e^{ik X_j} \mid N) \right)$$

Since the $e^{ik X_j}$ are independent r.v.s,

$$= \mathbb{E} \left(\prod_{j=1}^N \mathbb{E} e^{ik X_j} \right)$$

$$= \mathbb{E} \left(\prod_{j=1}^N \phi_X(k) \right) = \mathbb{E} \left((\phi_X(k))^N \right)$$

$$= G_N(\phi_X(k))$$

Be careful: G_N is not exactly a moment generating function.

What's true: $G_N(s) = \langle s^N \rangle = \langle e^{N \ln s} \rangle$

$$\langle N^n \rangle = \left(\frac{d}{d \ln s} \right)^n G_N(s) \Big|_{s=1} = \left(s \frac{d}{ds} \right)^n G_N(s) \Big|_{s=1}$$

$$\text{Or: } G_N'(s) = \langle N s^{N-1} \rangle$$

$$G_N''(s) = \langle N(N-1) s^{N-2} \rangle$$

$$G_N'(1) = \langle N \rangle = \mu_N$$

$$G_N''(1) = \langle N(N-1) \rangle = \langle N^2 \rangle - \langle N \rangle \\ = \sigma_N^2 + \mu_N^2 - \mu_N$$

Plug in the values for $\theta_x'(0)$, $\theta_x''(0)$, $G_N'(1)$, $G_N''(1)$ into the expressions for $\langle Z \rangle$, $\langle Z^2 \rangle$

$$\langle Z \rangle = \mu_x \mu_N$$

$$\sigma_Z^2 = \langle Z^2 \rangle - \langle Z \rangle^2 = \mu_x^2 \sigma_N^2 + \sigma_x^2 \mu_N$$

Another problem for HW1

- redo this calculation using
cumulant gen fns for $N, X,$

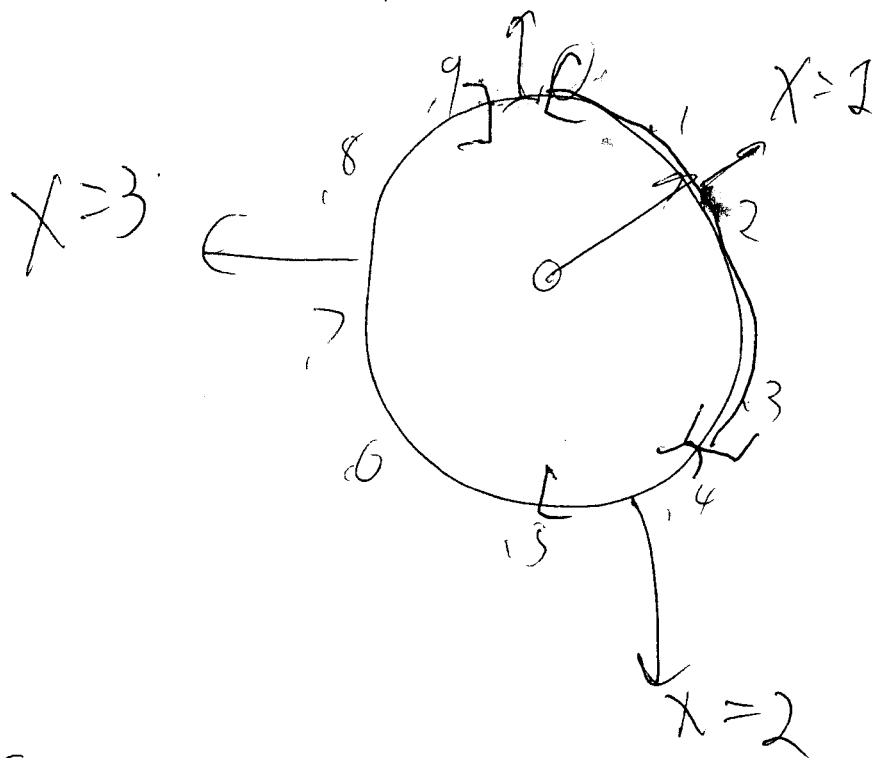
HW1 now due ^{Thursday} 02/05/04 at 5 PM,

Simulating discrete random variables.

Finite state space S .

Computer simulates "pseudo-random"
uniformly distributed random numbers
 $0 \leq x \leq 1$.

Let E_1, \dots, E_4



$$\text{Prob}(X=1) = .35$$

$$\text{Prob}(X=2) = .15$$

$$\text{Prob}(X=3) = .45$$

$$\text{Prob}(X=4) = .05$$

Some other considerations:

If complicated, think of breaking
up into simpler pieces.

Example: binomial dist

$$\text{Prob}(X=j) = \binom{N}{j} p^j (1-p)^{N-j}$$

$$N=1000$$

Poisson random variables a pain to simulate
this way

- but easy using stochastic process ideas!

What if the probability space or state space is uncountably big (~~not discrete~~),

- continuous random variable
- infinite # of discrete random variables,
- measure theory gets technical here.