

Lecture 5

N particles, M cells in space

Ideal: particles distribute uniformly in space and do not have any interaction

independence

Def'n: For any $H_k(\cdot)$

$$E\left[\prod_{k=1}^M H_k(X_k)\right] = \prod_{k=1}^M E[H_k(X_k)]$$

$\Leftrightarrow X_1, \dots, X_M$ are independent

$$\begin{aligned} &\Leftrightarrow P(X_1 \in A_1, X_2 \in A_2, \dots, X_M \in A_M) \\ &= P(X_1 \in A_1)P(X_2 \in A_2) \dots \\ &\quad \cdot P(X_M \in A_M) \end{aligned}$$

"Stock prices of two days are not indepdnt."

But in this class we have to assume lots of stuffs
Are independent.

Discrete Random Variables

① Bernoulli distributions

Counting

Combinations. If we have n objects, we select p out of them and we do not care about the order of them, then the total number of ways to select the p objects is called $\binom{n}{p} \leftarrow n \text{ choose } p$

$$\text{where } \binom{n}{p} = \frac{n!}{(n-p)!p!}$$

X is a Bernoulli(p) distribution if

$$X = \begin{cases} 1 & \text{w.p. } p \\ 0 & \text{w.p. } 1-p \end{cases} \quad (\text{proof as a homework})$$

w.p. with probability

\Rightarrow all indicator r.v.'s are Bernoulli.
 $\hookrightarrow I(\omega) = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \notin A \end{cases}$

If $X \sim \text{Bernoulli}(p)$,

$$\begin{aligned} E[X] &= 1 \times p + 0 \times (1-p) = p \\ \text{Var}[X] &= E[X^2] - (E[X])^2 = 1^2 \times p + 0^2 \times (1-p) - p^2 \\ &= p - p^2 \\ &= p(1-p) \end{aligned}$$

② Binomial distributions

Suppose we have n independent trials and each trial has probability p to succeed. Let X be the total number of successes, then X is called a binomial(n, p) random variable.

$$X \sim \text{Binomial}(n, p)$$

$$P(X=x) = ?$$

$x=0, 1, \dots, n \quad \dots (n+1) \text{ values to take}$

say have 2 successes at trial 2 & 3
then $(1-p) \cdot p \cdot p \cdot (1-p) \cdots (1-p)$ ↓
 $= p^x (1-p)^{n-x}$ (precondition: each trial is independent to others)
How many choices?
COMBINATION: $\binom{n}{x}$

Hence $P(X=x) = \binom{n}{x} p^x (1-p)^{n-x}$

Ex: Sps A has prob. of 0.6 of success in a game. And he plays this game 10 times independently. Calculate $P(X=2)$ where X is the number of winnings.

$$P(X=2) = \binom{10}{2} 0.6^2 0.4^8 = \dots$$

If $X \sim \text{Binomial}(n, p)$
 $E[X] = E[X_1 + X_2 + \dots + X_n] = p + p + \dots + p = np$ each of them is an expectation of a Bernoulli r.v.

To calculate $\text{Var}(X)$, need a lemma and a prop.

$$\text{Var}(X) = \text{Var}(X_1 + X_2 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n) = np(1-p)$$

Write $X = X_1 + X_2 + \dots + X_n$ where $X_i = \begin{cases} 1 & \text{if } i\text{th trial is a success} \\ 0 & \text{if } 0.w. \end{cases}$

Lemma: If X & Y are independent, then $\text{Cov}(H(X), G(Y)) = 0$ for any functions H & G .

Proof: $\text{Cov}(H(X), G(Y)) = E[H(X)G(Y)] - E[H(X)]E[G(Y)]$

By the def'n of independence, this = 0. done. ■

Proposition: If X_1, X_2, \dots, X_n are indep dt, then $\text{Var}[a_1 X_1 + a_2 X_2 + \dots + a_n X_n] = a_1^2 \text{Var}(X_1) + a_2^2 \text{Var}(X_2) + \dots + a_n^2 \text{Var}(X_n)$

Proof: $V[\sum a_i X_i] = E[(\sum a_i X_i - E[\sum a_i X_i])^2]$
 $= E[(\sum a_i (X_i - E X_i))^2]$

Let $Y_i = X_i - E X_i$
 $= E[(\sum a_i Y_i)^2]$
 $= E[\sum_{i=1}^n \sum_{j=1}^n a_i a_j Y_i Y_j]$

$$E[\sum_{i,j=1}^n a_i a_j Y_i Y_j] = \sum_{i,j=1}^n a_i a_j E(Y_i Y_j) = \sum_{i=1}^n a_i^2 \text{Var}(X_i)$$

$E(Y_i Y_j) = \begin{cases} 0 & \text{if } i \neq j \text{ since } E(Y_i) = 0 \\ V(X_i) & \text{if } i = j \end{cases}$

Ex (Warning!)

Suppose there are 30 black balls and 70 white balls in a box. Select 10 balls randomly from the box. Let X be then number of black ball.

$X \not\sim \text{Binomial}(10, 0.3)$ 10 draws are not independent

③

Geometric distributions

X is a Geometric random variable with success probability p , if X represents the

number of independent trials prior to the first success (p is the success prob for each single trial)

$$P(X=x) = P(\underbrace{FF \cdots FS}_{\text{failures}}) = P(F)P(F) \cdots P(F)P(S) = (1-p)^x p \quad x=0, 1, \dots$$

↑
Geometric (p)

$$EX = \sum_{x=0}^{\infty} x P(X=x) = \sum_{x=1}^{\infty} x(1-p)^x p = p \sum_{x=0}^{\infty} x q^x = p \frac{q}{(1-q)^2} = p \cdot \frac{q}{p^2} = \frac{q}{p}$$

$$\sum_{j=0}^{\infty} q^j = \frac{1}{1-q} \quad \sum_{j=0}^{\infty} j q^{j-1} = \frac{1}{(1-q)^2}$$

$$\Rightarrow \sum_{j=0}^{\infty} j q^j = \frac{q}{(1-q)^2}$$

$$\text{Var}[X] = EX^2 - (EX)^2 = EX^2 - q^2/p^2 = \sum_{x=0}^{\infty} x^2 q^x p - q^2/p^2 = p \left(\sum_{x=0}^{\infty} x^2 q^x \right) - q^2/p^2 = \dots \text{Crest as HW}$$

Variance of Geometric Distribution Proof With
Proof 1

From the definition of Variance as Expectation of Square minus Square of Expectation:

$$\text{var}(X) = E(X^2) - (E(X))^2$$

From Expectation of Function of Discrete Random Variable:

$$E(X^2) = \sum_{x \in \Omega_X} x^2 \Pr(X=x)$$

To simplify the algebra a bit, let $q = 1 - p$, so $p + q = 1$.

Thus:

$$\begin{aligned} E(X^2) &= \sum_{k \geq 1} k^2 q p^k && \text{Definition of geometric distribution, with } p+q=1 \\ &= p \sum_{k \geq 1} k^2 q p^{k-1} \\ &= p \left(\frac{2}{q^2} - \frac{1}{q} \right) && \text{from Proof 1 of Variance of Shifted Geometric Distribution} \end{aligned}$$

Then:

$$\begin{aligned} \text{var}(X) &= E(X^2) - (E(X))^2 \\ &= p \left(\frac{2}{(1-p)^2} - \frac{1}{1-p} \right) - \frac{p^2}{(1-p)^2} && \text{Expectation of Geometric Distribution: } E(X) = \frac{p}{1-p} \\ &= \frac{p}{(1-p)^2} && \text{after some algebra} \end{aligned}$$

Proof 2

From Variance of Discrete Random Variable from PGF, we have:

$$\text{var}(X) = \Pi''_X(1) + \mu - \mu^2$$

where $\mu = E(x)$ is the expectation of X .

From the Probability Generating Function of Geometric Distribution, we have:

$$\Pi_X(s) = \frac{q}{1-ps}$$

where $q = 1 - p$.

From Expectation of Geometric Distribution, we have:

$$\mu = \frac{p}{q}$$

From Derivatives of PGF of Geometric Distribution, we have:

$$\Pi''_X(s) = \frac{2qp^2}{(1-ps)^3}$$

Putting $s = 1$ using the formula $\Pi''_X(1) + \mu - \mu^2$:

$$\text{var}(X) = \frac{2qp^2}{(1-p)^3} + \frac{p}{q} - \left(\frac{p}{q} \right)^2$$

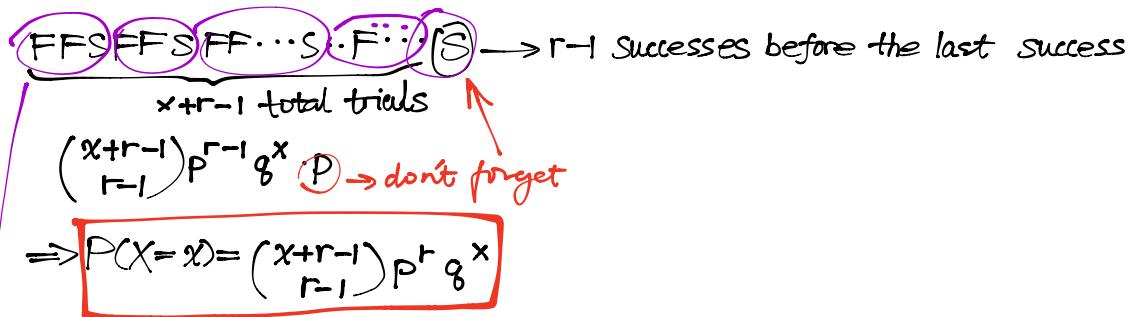
and hence the result, after some algebra.

(4)

The negative binomial distributions

X is called a negative binomial random variable with parameters p and r , if X represents the number of fails prior to the r th success, and each single trial is independent of one another and has probability p of success.

$$P(X=x)$$



$$\binom{x+r-1}{r-1} p^{r-1} q^x \quad (\text{P} \rightarrow \text{don't forget})$$

$$\Rightarrow P(X=x) = \binom{x+r-1}{r-1} p^r q^x$$

$$E[X] = ? \\ Var[X] = ?$$

"Think : negative bino = sum of geometrics"



$$X = Y_1 + Y_2 + \dots + Y_r$$

where Y_i is the # of trials between i th & $(i-1)$ th success.

Let the 0th success = 0

Hence

$$E[X] = E(Y_1) + E(Y_2) + \dots + E(Y_r) = \frac{rq}{p}$$

$$Var[X] = V[Y_1] + \dots + V[Y_r] = r \frac{q}{p^2}$$

Note: $\frac{V[X]}{E[X]} = \frac{rq/p^2}{rq/p} = \frac{1}{p} > 1$ *for Poisson, the ratio is 1

In statistics, if a data set shows $V[X]/E[X] > 1$, then one should consider a negative binomial model for the counts.

(5)

Poisson random variables

Ex suppose we want to model the number of car accidents in a week time. What we can do is that we divide this week time into n equal sized time blocks.

n is large that there is negligible chance that more than one accident will happen in each block.

Then X , the number of accidents equals $X_1 + \dots + X_n$ where X_i is # of accidents in the block. According to set up

$$X_i = \begin{cases} 1 & \text{w.p. } p_n \\ 0 & \text{w.p. } 1-p_n \end{cases}$$

Assume X_i 's are independent, then $X \sim \text{Binomial}(n, p_n)$

$$EX = n p_n = \lambda \quad \text{constant}$$

$$P(X=x) = \binom{n}{x} p_n^x (1-p_n)^{n-x} = \frac{n!}{(n-x)! x!} p_n^x (1-p_n)^{n-x}$$

~~4~~

$$= \frac{1}{x!} [n(n-1)(n-2)\cdots(n-x+1)] p_n^x (1-p_n)^{n-x}$$

Write $p_n = \lambda/n$ since $n p_n = \lambda$

$$= \frac{1}{x!} [n(n-1)\cdots(n-x+1)] \left(\frac{\lambda}{n}\right)^x \left(1 - \frac{\lambda}{n}\right)^{n-x}$$

$$= \frac{\lambda^x}{x!} \left[\frac{n(n-1)\cdots(n-x+1)}{n^x} \right] \left(1 - \frac{\lambda}{n}\right)^n / \left(1 - \frac{\lambda}{n}\right)^x$$

A B C

as $n \rightarrow \infty$, B $\rightarrow e^{-\lambda}$
 Recall: $(1 - \frac{\lambda}{n})^n \rightarrow e^{-\lambda}$

$$A = \frac{n}{n} \frac{n-1}{n} \frac{n-2}{n} \cdots \frac{n-x+1}{n}$$

C $\rightarrow 1$
 A $\rightarrow 1$

$$P(X=x) = \frac{\lambda^x}{x!} e^{-\lambda}$$

A Poisson r.v. with rate lambda has probability distribution \rightarrow ... Lambda must be positive.

Poisson distributions are frequently used to model counts.

HW: Show that if $X \sim \text{Poisson}(\lambda)$, then

① $E(X) = V(X) = \lambda$

② if X, Y are iid Pois(λ), then $X+Y \sim \text{Pois}(2\lambda)$

Midterm coverage: chapter 1 to chapter 4.2 except multinomial distributions but includes materials covered in the lectures but not in the textbooks, like dominant convergence theorem.

CALCULATOR!!!