## ISyE 3770, Spring 2024 Statistics and Applications

## Introduction to Discrete Distribution

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## Chapter 2.1 Discrete Distribution

Starting from this section, some typical random experiments and corresponding distribution will be introduced.

## Section 2.4 Binomial distribution

> Bernoulli experiment
The outcome can be classified in one of two mutually exclusive and exhaustive ways--say either success or failure. (e.g. female or male; life or death)
$>$ Bernoulli trials
When a Bernoulli experiment is performed several independent times and the probability of success-say, $p-$ remains the same from trial to trial. In other words, we let $p$ donate the probability of success on each trial. And we define $q \triangleq 1-p$ to donate the probability of failure.

## Example 1:

You are a fan of lottery. For a lottery, the probability of winning is $\frac{1}{1000}$. If you buy the lottery for 10 successive days,
that corresponds to 10 Bernoulli trials with $p=\frac{1}{1000}$. Assuming
> Bernoulli distribution

- Let $X$ be a RV associated with a Bernoulli trial with the probability of success $p$.
- Define RV

$$
\begin{aligned}
& X: S \rightarrow X(S) \subseteq \mathbb{R}, \quad S=\{\text { Success, Failure }\} \\
& X(\text { Success })=1, X(\text { Failure })=0, \quad X(S)=\{0,1\}
\end{aligned}
$$

- The pmf of $X$ can be written as:

$$
\begin{aligned}
& f: X(S)=\{0,1\} \rightarrow[0,1] \\
& x \mapsto f(x)=p^{x}(1-p)^{1-x}
\end{aligned}
$$

- The RV $X$ has a Bernoulli distribution with the following characteristic:

$$
\mathbb{E}[X]=p, \quad \operatorname{Var}[X]=p q, \quad M(t)=\mathbb{E}\left[e^{t X}\right]=(1-p)+p \cdot e^{t} .
$$

$>$ In a sequence of $n$ Bernoulli trials, we shall let $X_{i}$ denote the Bernoulli random variable associated with the $i$-th trial. An observed sequence of $n$ Bernoulli trials will then be an $n$ tuple of zeros and ones, and we often call this collection a random sample of size $n$ from a Bernoulli distribution

## Example 2

Out of millions of instant lottery tickets, suppose that $20 \%$ are winners. If 5 tickets are purchased, then $(0,0,0,1,0)$ is a random sample. Assuming independence between purchasing different tickets, the probability of this sample is

$$
p=(0.2)(0.8)^{4}
$$

## Multiplication Rule:

Suppose events $A_{1}, A_{2}, \ldots, A_{n}$ are mutually independent,

$$
P\left(A_{1} \cap \cdots \cap A_{n}\right)=P\left(A_{1}\right) \cdots P\left(A_{n}\right)
$$

## Binomial Distribution

- Motivation: We are interested in the number of successes in n Bernoulli trials, the order of the occurrence is not concerned.

A binomial experiment satisfies the following properties:

1. A Bernoulli experiment (i.e., Success \& Failure) is performed $n$ times.
2. Trials are independent.

Multiplication rule of probability:
$P(A \cap B)=P(A) P(B)$
3. Probability of success on each trial is a constant $p$; the probability of failure
is $q=1-p$.
4. Define RV $X$ as \# of successes in $n$ trials.

- $X: S \rightarrow X(S)=\{0,1, \ldots, n\}$.

Remark: $f(x)$ refers to binomial probability, $X$ is said to have a Binomial distribution, denoted as $X \sim b(n, p)$

- When $x \in X(S)$, \# of ways of selecting $x$ successes in $n$ trials is $\binom{n}{x}$.
- Since trials are independent, the probability of each way is $p(1-p)^{n-x}$.
- pmf of $X$ :

$$
f(x)=\binom{n}{x} p^{x}(1-p)^{n-x}, \quad x=0,1, \ldots, n .
$$

Why pmf is well-defined?

## Example 2 (revisited)

Let the probability of producing a winning ticket to be $20 \%$. If $X$ is the number of winning tickets, where $n=5$ tickets are purchased, then the probability of purchasing 2 winning tickets is

$$
f(2)=P(X=2)=\binom{5}{2}(0.2)^{2}(0.8)^{3}, \quad X \sim b(5,0.2) .
$$

$>$ cdf of Binomial distribution

- Assume $X$ have a Binomial distribution $b(n, p)$, the $\operatorname{cdf}$ of $X$ is

$$
F(x)=P(X \leq x)=\sum_{y \in X(S):} f(y \leq x)=\sum_{y=0}^{\lfloor x\rfloor}\binom{n}{y} p^{y}(1-p)^{n-y}
$$

Here $x \in(-\infty, \infty)$, and $\lfloor x\rfloor$ denotes the largest integer that is no more than $x$.

- Assume $X$ have a Binomial distribution $b(n, p)$, the cdf of $X$ is

$$
F(x)=P(X \leq x)=\sum_{y \in X(S): y \leq x} f(y)=\sum_{y=0}^{\lfloor x\rfloor}\binom{n}{y} p^{y}(1-p)^{n-y}
$$

## Example 3

Chickens are raised for laying eggs. Let $p=0.5$ be the probability that the newly hatched chick is a female. Assuming independence, let $X$ be the number of female chicks out of 10 newly hatched chicks selected at random.

- Obviously, $X \sim b(10,0,5)$. Compute

$$
P(X \leq 5), P(X=6), P(X \geq 6)
$$

Solution:

$$
\begin{aligned}
& P(X \leq 5)=\sum_{x=0}^{5}\binom{10}{x}(0.5)^{x}(0.5)^{10-x}, \quad P(X \geq 6)=1-P(X \leq 5) . \\
& P(X=6)=f(6)=\binom{10}{x}(0.5)^{6}(0.5)^{4} .
\end{aligned}
$$

## $>m g f$ of Binomial distribution

Assume $X$ have a binomial distribution $b(n, p)$, the mgf of $X$ is

$$
M(t)=\mathbb{E}\left[e^{t X}\right]=\sum_{x=0}^{n} e^{t x}\binom{n}{x} p^{x}(1-p)^{n-x}
$$



- $M^{\prime}(t)=n\left[(1-p)+p e^{t}\right]^{n-1} p e^{t}$, which implies

$$
M^{\prime}(0)=\mathbb{E}[X]=n p
$$

- $M^{\prime \prime}(t)=n(n-1)\left[(1-p)+p e^{t}\right]^{n-2}\left(p e^{t}\right)^{2}+n\left[(1-p)+p e^{t}\right]^{n-1} p e^{t}$, which implies

$$
M^{\prime \prime}(0)=\mathbb{E}\left[X^{2}\right]=n(n-1) p^{2}+n p .
$$

- $\operatorname{Var}[X]=\mathbb{E}\left[X^{2}\right]-(\mathbb{E}[X])^{2}=n p(1-p)$.

Besides, when $n=1$, the Binomial distribution reduces to Bernoulli distribution.

## Section 2.5

## Negative Binomial distribution

- Motivation: We are interested in the situation that we observe a sequence of independent Bernoulli trials until exactly $r$ successes occur, where $r$ is a fixed positive integer.
- Define RV $X$ to be the trial number, on which the $r$-th success is observed.

$$
X: S \rightarrow X(S)=\{r, r+1, \ldots\}
$$

- Let $f(x)$ denote the pmf of $X$.
$f(x)=P(\{$ At the $x$-th trial, $r$-th success is observed $\})$
$=P(\{$ for the first $x-1$ trials, $r-1$ success have been observed $\}\}$

$$
\begin{aligned}
& P(A)=\binom{x-1}{r-1} p^{r-1}(1-p)^{x-r}, \quad P(B)=p . \\
& \Longrightarrow \\
& \\
& f(x)=\binom{x-1}{r-1} p^{r}(1-p)^{x-r}, \quad x=r, r+1, \ldots
\end{aligned}
$$

## Special Case of Negative Binomial Distribution for $r=1$

- $f(x)=p(1-p)^{x-1}$.
- For fixed $k \in \mathbb{N}_{+}$,

$$
\begin{aligned}
& P(X>k)=\sum_{x=k+1}^{\infty} p(1-p)^{x-1}=\frac{p(1-p)^{k}}{1-(1-p)}=(1-p)^{k} . \\
& P(X \leq k)=1-P(X>k)=1-(1-p)^{k}
\end{aligned}
$$

## Example 1

- Biology students are checking eye color of fruit flies.
- For individual fly, $P$ (white) $=1 / 4, P($ red $)=3 / 4$.
- Assume the observations are independent Bernoulli trials.

At least 4 Flies: $\quad P(X \geq 4)=P(X>3)=(1-1 / 4)^{3}=(3 / 4)^{3}$
At most 4 Flies: $\quad P(X \leq 4)=1-(1-1 / 4)^{4}$
4 Flies: $\quad P(X=4)=(1 / 4)(3 / 4)^{3}$

## $>$ Mean and Variance

Prove the following for $X$ having a negative binomial distribution:

$$
\mathbb{E}[X]=\frac{r}{p}, \quad \operatorname{Var}[X]=\frac{r(1-p)}{p^{2}}
$$

Proof: The mgf of $X$ is

- Direct Calculation
- Using mgf
$M(t)=\mathbb{E}\left[e^{t X}\right]=\sum_{x=r}^{\infty} e^{t x}\binom{x-1}{r-1} p^{r}(1-p)^{x-r}=\left(p e^{t}\right)^{r} \sum_{x=r}^{\infty}\binom{x-1}{r-1}\left[(1-p) e^{t}\right]^{x-r}$

$$
=\frac{\left(p e^{t}\right)^{r}}{\left[1-(1-p) e^{t}\right]^{r}}, \quad \text { where }(1-p) e^{t}<1
$$

Therefore,

$$
\begin{gathered}
M^{\prime}(t)=r\left(p e^{t}\right)^{r}\left[1-(1-p) e^{t}\right]^{-r-1} \\
M^{\prime \prime}(t)=r\left(p e^{t}\right)^{r}(-r-1)\left[1-(1-p) e^{t}\right]^{-r-2}\left[-(1-p) e^{t}\right] \\
+r^{2}\left(p e^{t}\right)^{r-1}\left(p e^{t}\right)\left[1-(1-p) e^{t}\right]^{-r-1} \\
\Longrightarrow \mathbb{E}[X]=M^{\prime}(0)=r p^{-1}, \quad \mathbb{E}\left[X^{2}\right]=M^{\prime \prime}(0)=r p^{-2}(r+1-p) . \\
\Longrightarrow \operatorname{Var}[X]=\mathbb{E}\left[X^{2}\right]-(\mathbb{E}[X])^{2}=r p^{-2}(1-p) .
\end{gathered}
$$

Section 2.6 Poisson Distribution
There are experiments that result in counting the number of times particular events occur at given times or with given physical objects.

- The number of flaws in a 100 feet long
E.g. wire
- The number of customers that arrive at a ticket window between 9 p.m. to 10 p.m.

Counting such events can be looked upon as observations of a random variable associated with an approximate Poisson process(APP), provided that the conditions in the following definition are satisfied.

## Definition [ Approximate Possion Process (App)]

Let the number of occurrences of some event in a given continuous interval be counted. Then we have an APP with parameter $\lambda \geq 0$ if
(a) The numbers of occurrences in nonoverlapping subintervals are independent.
(b) The probability of exactly one occurrence in a sufficiently short subinterval of length $h$ is approximately $\lambda h$.
(c) The probability of two or more occurrences in a sufficiently short subinterval is essentially 0 .

Consider a random experiment desired by App. Let $X$ denote the number of occurrences in an interval of length 1 . We aim to find an approximation for $P(X=x)$, where $x$ is a nonnegative integer.
(1) Partition the interval
into a number of
nonoverlapping

subintervals $\quad$| $\frac{1}{n} \frac{1}{n} \frac{1}{n}$ |
| :--- | :--- | :--- |

(2) If $n$ is sufficiently large $(n \gg x), P(X=x)$ can be approximated by the probability that exactly x of these n subintervals each has one occurrence.
(3) I. By condition (b), the probability of one occurrence in anyone subinterval of length $1 / n$ is approximately $\lambda / n$.
II. By condition (c), the probability of 2 or more occurrences in any one subinterval is essentially 0 . That is, For each subinterval there is either no occurrence or one occurrence. [The probability of occurrence is $\frac{\lambda}{n}$.
Conditions I and II implies that the occurrence and non-occurrence in each interval can be treated as Bernoulli trials.
III. By condition (a), we have a sequence of $n$ Bernoulli trials with probability $p$ approximately equal to $\frac{\lambda}{n}$.

Number of Occurrence follows $b\left(1, \frac{\lambda}{n}\right)$
(4) Therefore, $P(X=x)$ can be approximated by the binomial probability:

$$
P(X=x) \approx \frac{n!}{x!(n-x)!}\left(\frac{\lambda}{n}\right)^{x}\left(1-\frac{\lambda}{n}\right)^{n-x}
$$

(5) If let $n \rightarrow \infty$, then

$$
\lim _{n \rightarrow \infty} \frac{n!}{x!(n-x)!}\left(\frac{\lambda}{n}\right)^{x}\left(1-\frac{\lambda}{n}\right)^{n-x}=\lim _{n \rightarrow \infty} \frac{n!}{(n-x)!n^{x}} \cdot \frac{\lambda^{x}}{x!}\left(1-\frac{\lambda}{n}\right)^{n}\left(1-\frac{\lambda}{n}\right)^{-x}
$$

Now for fixed $n$, we have:

$$
\lim _{n \rightarrow \infty} \frac{n!}{(n-x)!n^{x}}=\lim _{n \rightarrow \infty} \frac{n(n-1) \cdots(n-x+1)}{n^{x}}=\lim _{n \rightarrow \infty}\left[1 \cdot\left(1-\frac{1}{n}\right) \cdots\left(1-\frac{x-1}{n}\right)\right]=1,
$$

$$
\lim _{n \rightarrow \infty}\left(1-\frac{\lambda}{n}\right)^{n}=e^{-\lambda}, \lim _{n \rightarrow \infty}\left(1-\frac{\lambda}{n}\right)^{-x}=1
$$

$$
\text { We have } P(X=x)=\lim _{n \rightarrow \infty} \frac{n!}{(n-x)!n^{x}} \cdot \frac{\lambda^{x}}{x!}\left(1-\frac{\lambda}{n}\right)^{n}\left(1-\frac{\lambda}{n}\right)^{-x}=\frac{\lambda^{x} e^{-\lambda}}{x!} \text {. }
$$

Since we know $\lim _{n \rightarrow \infty}\left(1+\frac{x}{n}\right)^{n}=e^{x}$, we replace $x$ with $-\lambda$.

## Definition 2.6-2 [Poisson distribution]

It can be verified that

$$
f(x)=\frac{\lambda^{x} e^{-\lambda}}{x!}, \quad x=0,1, \ldots
$$

What is the interpretation of $\lambda$ ?
is a well-defined pmf. If a $\mathrm{RV} X$ has $f(x)$ as its $p m f$, then $X$ is said to have a Poisson distribution.
$>$ Mean and Variance
The mgf of a Poisson distribution for a RV $X$ is

$$
\left.\begin{array}{l}
M(t)=\mathbb{E}\left[e^{t X}\right]=\sum_{x=0}^{\infty} e^{t x} \frac{\lambda^{x} e^{-\lambda}}{x!}=e^{-\lambda} \sum_{x=0}^{\infty} \frac{\left(\lambda e^{t}\right)^{x}}{x!} \\
=e^{-\lambda} e^{\lambda e^{t}}=e^{\lambda\left(e^{t}-1\right)} . \begin{array}{l}
\lambda \text { is the average } \\
\text { number, or variance } \\
\text { of occurrences in the }
\end{array} \\
\text { interval. }
\end{array}\right\} \begin{aligned}
& M^{\prime}(t)=\lambda e^{t} e^{\lambda\left(e^{t}-1\right)} \Longrightarrow M^{\prime}(0)=\lambda=\mathbb{E}[X] \quad \begin{array}{l}
\text { in }
\end{array} \\
& M^{\prime \prime}(t)=\lambda e^{t} e^{\lambda\left(e^{t}-1\right)}+\lambda^{2} e^{2 t} e^{\lambda\left(e^{t}-1\right)} \Longrightarrow M^{\prime \prime}(0)=\lambda+\lambda^{2}=\mathbb{E}\left[X^{2}\right] \\
& \operatorname{Var}[X]=\mathbb{E}\left[X^{2}\right]-(\mathbb{E}[X])^{2}=\lambda
\end{aligned}
$$

## Example 1

In a large city, telephone calls to 110 come on the average of 2 every 3 minutes. If one models with App , what is the probability of five or more calls arriving in a 9-minute period?

Solution. Let $X$ denote the number of calls in a 9 -min period. Then $\mathbb{E}[X]=6=\lambda$, which implies $f(x)=\frac{6^{x} e^{-6}}{x!}$. Hence, $P(X \geq 5)=1-P(X \leq 4)=1-\sum_{x=0}^{4} \frac{6^{x} e^{-6}}{x!}$.

