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## 1 Binomial Random Variable: Mean and Variance

We say that a random variable $X$ is binomially distributed with probability $p$, and write $X \sim \operatorname{Bin}(n, p)$, if its probability mass function (pmf) is given as follows:

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

Here, $X$ counts the total number of successes (1's) in $n$ independent and identically distributed Bernoulli experiments, where the probability of success (or 1) at each experiment is $p$. Consequently, we can write $X=\sum_{i=1}^{n} X_{i}$ where each $X_{i} \sim \operatorname{Bernoulli}(p)$.

The mean of each Bernoulli component can be computed as follows:

$$
E\left(X_{i}\right)=0(1-p)+1 p=0+p=p
$$

and from here,

$$
E(X)=\sum_{i=1}^{n} E\left(X_{i}\right)=\sum_{i=1}^{n} p=n p
$$

Similarly, the variance of each Bernoulli component can be computed as follows:

$$
V\left(X_{i}\right)=(0-p)^{2}(1-p)+(1-p)^{2} p=p^{2}(1-p)+(1-p)^{2} p=p(1-p)(p+1-p)=1(1-p)
$$

and from here,

$$
V(X)=\sum_{i=1}^{n} V\left(X_{i}\right)=\sum_{i=1}^{n} p(1-p)=n p(1-p)
$$

We can simply sum the variances of the Bernoulli variables because they are all independent.
Alternatively, we can find the mean using some simple algebra and the Binomial Theorem:

$$
\begin{gathered}
E(X)=\sum_{x=0}^{n} x\binom{n}{x} p^{x}(1-p)^{(n-x)}= \\
=\sum_{x=0}^{n} x \frac{n!}{x!(n-x)!^{x}(1-p)^{(n-x)}=} \\
=n p \sum_{x=1}^{n} \frac{(n-1)!}{(x-1)!(n-x)!} p^{(x-1)}(1-p)^{(n-x)} \\
=n p \sum_{y=0}^{n-1} \frac{(n-1)!}{y!(n-1-y)!} p^{y}(1-p)^{(n-1-y)}=n p
\end{gathered}
$$

Similarly, we can find the mean using some simple algebra and the Binomial Theorem:

$$
V(X)=E\left(X^{2}\right)-E(X)^{2}=E(X(X-1))+E(X)-E(X)^{2}=
$$

$$
\begin{gathered}
=\sum_{x=2}^{n} x(x-1)\binom{n}{x} p^{x}(1-p)^{(n-x)}+n p-n^{2} p^{2}= \\
=\sum_{x=2}^{n} x(x-1) \frac{n!}{x!(n-x)!^{x}} p^{x}(1-p)^{(n-x)}+n p-n^{2} p^{2}= \\
=n(n-1) p^{2} \sum_{x=2}^{n} \frac{(n-2)!}{(x-2)!(n-x)!} p^{(x-2)}(1-p)^{(n-x)}+n p-n^{2} p^{2} \\
=n(n-1) p^{2} \sum_{y=0}^{n-2} \frac{(n-2)!}{y!(n-2-y)!} p^{y}(1-p)^{(n-2-y)}= \\
=n(n-1) p^{2}+n p-n^{2} p^{2}=n p(1-p)
\end{gathered}
$$

## 2 Negative Binomial Random Variable: Mean and Variance

We say that a random variable $X$ is negative-binomial with probability $p$ and parameter $r$, and write $X \sim \operatorname{NegBin}(r, p)$, if its probability mass function ( pmf ) is given as follows:

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

Here, $X$ counts the total number of failures ( 0 's) before observing $r$-th success in a sequence of independent and identically distributed Bernoulli experiments where the probability of success (or 1) at each experiment is $p$.

Alternatively, we can write $X=\sum_{i=1}^{r} X_{i}$ where each independent $X_{i} \sim \operatorname{Geom}(p)$ counts the number of failures between $(i-1)$ st and $i$ th success.

The mean of a Negative Binomial random variable can be computed as follows:

$$
\begin{gathered}
E(X)=\sum_{x=0}^{\infty} x\binom{r+x-1}{x} p^{r}(1-p)^{x}= \\
\sum_{x=1}^{\infty} \frac{(r+x-1)!}{(x-1)!(r-1)!} p^{r}(1-p)^{x}= \\
\frac{r(1-p)}{p} \sum_{x=1}^{\infty} \frac{(r+x-1)!}{(x-1)!r!} p^{(r+1)}(1-p)^{(x-1)}= \\
\frac{r(1-p)}{p} \sum_{y=0}^{\infty}\binom{r+1+y-1}{y} p^{(r+1)}(1-p)^{y}= \\
=\frac{r(1-p)}{p}
\end{gathered}
$$

The variance is computed in a similar way.

## 3 Poisson Random Variable: Mean and Variance

A random variable $X$ is said to be Poisson distributed with mean $\lambda$ if its pmf is given as

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

for any $x=0,1, \ldots \infty$.
The mean of a Poisson random variable can be found via:

$$
\begin{aligned}
& E(X)=\sum_{x=0}^{\infty} x e^{-\lambda} \frac{\lambda^{x}}{x!}=\sum_{x=1}^{\infty} x e^{-\lambda} \frac{\lambda^{x}}{x!}= \\
& =\sum_{x=1}^{\infty} e^{-\lambda} \frac{\lambda^{x}}{(x-1)!}=\lambda \sum_{y=0}^{\infty} e^{-\lambda} \frac{\lambda^{y}}{y!}=\lambda
\end{aligned}
$$

And similarly, the variance can be found via:

$$
\begin{gathered}
E(X(X-1))=\sum_{x=0}^{\infty} x(x-1) e^{-\lambda} \frac{\lambda^{x}}{x!}=\sum_{x=2}^{\infty} x(x-1) e^{-\lambda} \frac{\lambda^{x}}{x!}= \\
=\sum_{x=2}^{\infty} e^{-\lambda} \frac{\lambda^{x}}{(x-2)!}=\lambda^{2} \sum_{y=0}^{\infty} e^{-\lambda} \frac{\lambda^{y}}{y!}=\lambda^{2}
\end{gathered}
$$

From here,

$$
V(X)=E(X(X-1))+E(X)-E(X)^{2}=\lambda^{2}+\lambda-\lambda^{2}=\lambda
$$

