# Lecture Stat 302 <br> Introduction to Probability - Slides 19 

## AD

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## Sum of Independent Random Variables

- Consider $Z=X+Y$ where $X$ and $Y$ are disrete r.v. of respective p.m.f. $p_{X}(x)$ and $p_{Y}(y)$ then

$$
p_{Z}(z)=\sum_{y} p_{X}(z-y) p_{Y}(y)
$$

- Consider $Z=X+Y$ where $X$ and $Y$ are continuous r.v. of respective p.d.f. $f_{X}(x)$ and $f_{Y}(y)$ then

$$
f_{Z}(z)=\int_{-\infty}^{\infty} f_{X}(z-y) f_{Y}(y) d y
$$

## Sum of Exponential Random Variables

- Consider two independent exponential r.v. $X, Y$ of parameter $\lambda$ (i.e. $\left.f_{X}(x)=f_{Y}(x)=\lambda e^{-\lambda x} 1_{[0, \infty)}(x)\right)$.
- The pdf of $Z=X+Y$ is $f_{Z}(z)=0$ for $z<0$ and for $z>0$

$$
\begin{aligned}
f_{Z}(z) & =\int_{-\infty}^{\infty} \lambda e^{-\lambda(z-y)} 1_{[0, \infty)}(z-y) \lambda e^{-\lambda y} 1_{[0, \infty)}(y) d y \\
& =\lambda^{2} e^{-\lambda z} \int_{0}^{\infty} 1_{[0, \infty)}(z-y) d y \\
& =\lambda^{2} e^{-\lambda z} \int_{0}^{z} 1_{[0, \infty)}(z-y) d y \\
& =\lambda^{2} z e^{-\lambda z}
\end{aligned}
$$

## Sum of Gaussian Random Variables

- Consider two independent normal standard r.v. $X, Y$ (i.e. $\left.f_{X}(x)=f_{Y}(x)=\frac{1}{\sqrt{2 \pi}} e^{-x^{2} / 2}\right)$ then the pdf of $Z=X+Y$ is

$$
f_{Z}(z)=\frac{1}{2 \pi} \int_{-\infty}^{\infty} e^{-(z-y)^{2} / 2} e^{-y^{2} / 2} d y
$$

where

$$
\begin{aligned}
(z-y)^{2}+y^{2} & =z^{2}+2 y^{2}-2 y z \\
& =z^{2}+2(y-z / 2)^{2}-z^{2} / 2=2(y-z / 2)^{2}+z^{2} / 2
\end{aligned}
$$

- So we have

$$
f_{Z}(z)=\frac{e^{-z^{2} / 4}}{2 \pi} \sqrt{\pi} \int_{-\infty}^{\infty} \frac{1}{\sqrt{\pi}} e^{-(y-z / 2)^{2}} d y=\frac{e^{-z^{2} / 4}}{\sqrt{2 \pi} \sqrt{2}}
$$

Hence $Z$ is a normal r.v. of mean 0 and variance 2 .

- Generalization: if $X$ is an normal r.v. $\left(\mu_{X}, \sigma_{X}^{2}\right)$ and $Y$ is an normal r.v. $\left(\mu_{Y}, \sigma_{Y}^{2}\right)$ where $X$ and $Y$ are independent then $Z$ is a normal r.v. $\left(\mu_{X}+\mu_{Y}, \sigma_{X}^{2}+\sigma_{Y}^{2}\right)$.


## Conditional Distributions: Discrete Case

- Given a joint p.m.f. for two r.v. $X, Y$ it is possible to compute the conditional p.m.f. $X$ given $Y=y$.
- Assume $X, Y$ are discrete-valued r.v. with a joint p.m.f. $p(x, y)$ then the conditional p.m.f. of $X$ given $Y=y$ is

$$
\begin{aligned}
p_{X \mid Y}(x \mid y) & :=P(X=x \mid Y=y) \\
& =\frac{P(X=x \cap Y=y)}{P(Y=y)} \\
& =\frac{p(x, y)}{p_{Y}(y)} .
\end{aligned}
$$

- In the case where $X$ and $Y$ are independent, we have $p_{X \mid Y}(x \mid y)=p_{X}(x)$ as $p(x, y)=p_{X}(x) p_{Y}(y)$.


## Conditional Distributions: Discrete Case

- We have

$$
p(x, y)=p_{X \mid Y}(x \mid y) p_{Y}(y)
$$

and similarly

$$
p(x, y)=p_{Y \mid X}(y \mid x) p_{X}(x)
$$

- Hence we obtain

$$
p_{X \mid Y}(x \mid y)=\frac{p_{Y \mid X}(y \mid x) p_{X}(x)}{p_{Y}(y)}
$$

which holds if $p_{Y}(y)>0$.

## Conditional Expectation and Variance: Discrete Case

- We can define the mean, variance of the conditional p.m.f.
- The conditional mean is given by

$$
E(X \mid Y=y)=\sum_{x} x \cdot p_{X \mid Y}(x \mid y)
$$

- The conditional variance is given by

$$
\begin{aligned}
\operatorname{Var}(X \mid Y=y) & =E\left((X-E(X \mid Y=y))^{2} \mid Y=y\right) \\
& =E\left(X^{2} \mid Y=y\right)-\{E(X \mid Y=y)\}^{2}
\end{aligned}
$$

where

$$
E\left(X^{2} \mid Y=y\right)=\sum_{x} x^{2} \cdot p_{X \mid Y}(x \mid y)
$$

- $E(X \mid Y=y)$ and $\operatorname{Var}(X \mid Y=y)$ are functions but $E(X \mid Y)$ and $\operatorname{Var}(X \mid Y)$ are random variables.


## Example: Toy problem

- Consider $X \in\{0,1,2\}$ and $Y \in\{0,1,2\}$ such that their joint pmf is given by

| $y$ |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  |  |  |  |  |$|$| 0 | 1 | 2 |  |
| :--- | :--- | :--- | :--- |
| 0 | $1 / 9$ | $2 / 9$ | $1 / 9$ |
| 1 | $2 / 9$ | $2 / 9$ | 0 |
| 2 | $1 / 9$ | 0 | 0 |

- The conditional pmf of $X$ given $Y=0$ and $Y=1$ are

$$
p_{X \mid Y}(x \mid 0)=\frac{p(x, y=0)}{1 / 9+2 / 9+1 / 9}, p_{X \mid Y}(x \mid 1)=\frac{p(x, y=1)}{2 / 9+2 / 9+0} .
$$

- We have

$$
\begin{aligned}
E(X \mid 0) & =1 \times p_{X \mid Y}(x \mid 0)+2 \times p_{X \mid Y}(x \mid 0) \\
& =\frac{2 / 9}{4 / 9}+2 \times \frac{1 / 9}{4 / 9}=1
\end{aligned}
$$

## Example: Fair Die

- Roll a die until we get a 6 . Let $Y$ be the total number of rolls and $X$ the number of 1 's we get. What is the conditional pmf $p_{X \mid Y}(x \mid y)$ ? Compute $E(X \mid y)$ and $\operatorname{Var}(X \mid Y=y)$.
- The event $Y=y$ means that there were $y-1$ rolls that were not a 6 and then the $y$ th roll was a six.
- So $p_{X \mid Y}(x \mid y)$ is a binomial distribution with $n=y-1$ trials and proba. of success $p=1 / 5$.
- It follows that

$$
\begin{aligned}
E(X \mid y) & =n p=\frac{(y-1)}{5} \\
\operatorname{Var}(X \mid y) & =n p(1-p)=\frac{4(y-1)}{25}
\end{aligned}
$$

- If we do not observe $Y=y$, then $E(X \mid Y)=\frac{Y-1}{5}$ and $\operatorname{Var}(X \mid Y)=\frac{4(Y-1)}{25}$ are not numbers but random variables.


## Example: Fair Die

- As $E(X \mid Y)$ is a random variable, it is possible to compute its expectation

$$
\begin{aligned}
E(E(X \mid Y)) & =\sum_{y} E(X \mid Y=y) \cdot p_{Y}(y) \\
& =\sum_{y} \frac{(y-1)}{5} \cdot p_{Y}(y) \\
& =-\frac{1}{5}+\sum_{y} y p_{Y}(y)=-\frac{1}{5}+E(Y) \\
& =-\frac{1}{5}+6 \text { as } Y \text { Geometric }
\end{aligned}
$$

- It can actually be easily established that

$$
E(E(X \mid Y))=E(X)
$$

## Example: Poisson random variables

- Consider two Poisson independent r.v. $X$ and $Y$ of respective p.m.f. $p_{X}(x)=e^{-\lambda} \frac{\lambda^{x}}{x!}$ for $x=0,1,2, \ldots$ and $p_{Y}(y)=e^{-\lambda^{\prime}} \frac{\lambda^{\prime y}}{y!}$. Calculate the conditional p.m.f. of $X$ given $X+Y=m$. What is the conditional expectation and variance $E(X \mid y)$ and $\operatorname{Var}(X \mid y)$ ?
- We have $p(X=x \mid X+Y=m)=0$ for $x>m$ and for $x \leq m$

$$
\begin{aligned}
& p(X=x \mid X+Y=m)=\frac{p(X=x, X+Y=m)}{p(X+Y=m)} \\
& =\frac{p(X=x, Y=m-x)}{p(X+Y=m)}=\frac{p_{X}(X=x) p_{Y}(Y=m-x)}{p(X+Y=m)} \\
& =\frac{e^{-\lambda \frac{\lambda^{x}}{x!} e^{-\lambda^{\prime}} \frac{\left(\lambda^{\prime}\right)^{m-x}-x}{(m-x)!}}}{e^{-\left(\lambda+\lambda^{\prime}\right)} \frac{\left(\lambda+\lambda^{\prime}\right)}{m!}} \text { as } X+Y \text { is Poisson } \lambda+\lambda^{\prime} \\
& =\binom{m}{x} \frac{\lambda^{\times}\left(\lambda^{\prime}\right)^{m-x}}{\left(\lambda+\lambda^{\prime}\right)^{m}}=\binom{m}{x}\left(\frac{\lambda}{\lambda+\lambda^{\prime}}\right)^{x}\left(1-\frac{\lambda}{\lambda+\lambda^{\prime}}\right)^{m-x}
\end{aligned}
$$

which is a Binomial of parameter $n=m$ and success proba $p=\lambda /\left(\lambda+\lambda^{\prime}\right)$.

## Example: Poisson random variables

- Hence we have

$$
E(X \mid X+Y=m)=n p=\frac{m \lambda}{\left(\lambda+\lambda^{\prime}\right)}
$$

- We also obtain

$$
\begin{aligned}
\operatorname{Var}(X \mid X+Y=m) & =n p(1-p) \\
& =\frac{m \lambda \lambda^{\prime}}{\left(\lambda+\lambda^{\prime}\right)^{2}}
\end{aligned}
$$

## Example: How Many Tax Fraudsters?

- The number $N$ of tax fraudsters is assumed to follow a Poisson distribution with param $\lambda$. Each tax fraudster is identified with proba $p$ independently of the other fraudsters. Let $K$ be the number of fraudsters identified. What is the conditional p.m.f. of $N$ given $K=k$ ? Compute $E(N \mid k)$.
- We have

$$
\begin{aligned}
p_{N}(n) & =e^{-\lambda} \frac{\lambda^{n}}{n!} \\
p_{K \mid N}(k \mid n) & =\binom{n}{k} p^{k}(1-p)^{n-k}
\end{aligned}
$$

- We want to compute

$$
p_{N \mid K}(n \mid k)=\frac{p_{K \mid N}(k \mid n) p_{N}(n)}{p_{K}(k)}
$$

## Example: How Many Tax Fraudsters?

- We have $p_{N \mid K}(n \mid k)=0$ if $n<k$.
- If $n \geq k$

$$
\begin{aligned}
p_{N \mid K}(n \mid k) & =\frac{\binom{n}{k} p^{k}(1-p)^{n-k} e^{-\lambda} \frac{\lambda^{n}}{n!}}{\sum_{m \geq k}\binom{m}{k} p^{k}(1-p)^{m-k} e^{-\lambda \frac{\lambda^{m}}{m!}}} \\
& =\frac{\{(1-p) \lambda\}^{n-k}}{(n-k)!} e^{-(1-p) \lambda}(\text { use } i=m-k)
\end{aligned}
$$

- Hence we have

$$
E(N \mid k)=\sum_{n \geq k} n \frac{\{(1-p) \lambda\}^{n-k}}{(n-k)!} e^{-(1-p) \lambda}=k+(1-p) \lambda
$$

