# Chapter 6 - Lecture 2 <br> The distribution of a linear combination 

Yuan Huang

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(1) Definition of linear combination
(2) General Populations For general sample Special case for iid random sample Examples
(3) Normal Populations

For general normal random variables
For iid normal random sample
(4) Introduce another tool to derive distribution Normal case
Poisson case
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## Definition of Linear Combination

We have

- a random sample $X_{1}, X_{2}, \ldots, X_{n}$
- $n$ constants $a_{1}, \ldots, a_{n}$
then the random variable

$$
\begin{equation*}
Y=a_{1} X_{1}+\ldots+a_{n} X_{n}=\sum_{i=1}^{n} a_{i} X_{i} \tag{1}
\end{equation*}
$$

is called a linear combination of $X$ 's.

Many statistics are linear functions of the sample data $X_{1}, \ldots, X_{n}$ :

$$
Y=a_{1} X_{1}+\ldots+a_{n} X_{n}=\sum_{i=1}^{n} a_{i} X_{i}
$$

(1) $\bar{X}=\frac{1}{n} X_{1}+\ldots+\frac{1}{n} X_{n}$;

By learning properties of linear combination, we can get a clearer view of how a statistic is distributed.

## For general sample

## Proposition 1

$$
E\left(\sum_{i=1}^{n} a_{i} X_{i}\right)=a_{1} E\left(X_{1}\right)+a_{2} E\left(X_{2}\right)+\ldots+a_{n} E\left(X_{n}\right)
$$

- This proposition holds no matter whether the $X_{i}$ 's are independent or not.
- Interpretation, the sampling distribution of $\sum_{i=1}^{n} a_{i} X_{i}$ has mean $a_{1} E\left(X_{1}\right)+a_{2} E\left(X_{2}\right)+\ldots+a_{n} E\left(X_{n}\right)$.
- In most general case, each $X_{i}$ has expectation $\mu_{i}$, then

$$
E\left(\sum_{i=1}^{n} a_{i} X_{i}\right)=a_{1} \mu_{1}+a_{2} \mu_{2}+\ldots+a_{n} \mu_{n}
$$

## Practice: If $E\left(X_{1}\right)=2$ and $E\left(X_{2}\right)=3$ and $E\left(X_{3}\right)=1$ then

- $E\left(X_{1}-X_{2}\right)$ ?
- $E\left(X_{1}+X_{2}-X_{3}\right)$ ?
- $E(\bar{X})$ ?


## For general sample

## Proposition 2:

$$
V\left(a_{1} X_{1}+\ldots+a_{n} X_{n}\right)=\sum_{i=1}^{n} \sum_{j=1}^{n} a_{i} a_{j} \operatorname{Cov}\left(X_{i}, X_{j}\right)
$$

## For general sample

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Note that
(1) $\operatorname{Cov}\left(X_{i}, X_{i}\right)=V\left(X_{i}\right)$;
(2) If $X_{i}$ and $X_{j}$ are independent, $\operatorname{Cov}\left(X_{i}, X_{j}\right)=0$ (uncorrelated);

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Corollary
If $X_{1}, \ldots, X_{n}$ are mutually independent, then

$$
V\left(\sum_{i=1}^{n} a_{i} X_{i}\right)=\sum_{i=1}^{n} a_{i}^{2} V\left(X_{i}\right)
$$

## Special case for iid random sample

We have a random sample $X_{1}, X_{2}, \ldots, X_{n}$ from a distribution with mean $\mu$ and variance $\sigma^{2}$, and let $Y=\sum_{i=1}^{n} a_{i} X_{i}$ then:

$$
\mu_{Y}=\sum_{i=1}^{n} a_{i} \mu=\mu \sum_{i=1}^{n} a_{i}
$$

and

$$
\sigma_{Y}^{2}=\sum_{i=1}^{n} a_{i}^{2} \sigma^{2}=\sigma^{2} \sum_{i=1}^{n} a_{i}^{2}
$$

## Example

If we have $X_{1}$ and $X_{2}$ that $X_{1}$ has mean $\mu_{1}$ and variance $\sigma_{1}^{2}, X_{2}$ has mean $\mu_{2}$ and variance $\sigma_{2}^{2}$
(1) What is $E\left(X_{1}+X_{2}\right)$ and $V\left(X_{1}+X_{2}\right)$, when

- If $X_{1}, X_{2}$ are independent:
- If $X_{1}, X_{2}$ are dependent:
(2) What is $E\left(X_{1}-X_{2}\right)$ and $V\left(X_{1}-X_{2}\right)$, when
- If $X_{1}, X_{2}$ are independent:
- If $X_{1}, X_{2}$ are dependent:


## Examples

## Example 6.11 page 301

A gas station sells three grades of gasoline: regular unleaded, extra unleaded, and super unleaded. These are priced at $\$ 2.20, \$ 2.35$, $\$ 2.50$ per gallon, respectively. Let $X_{1}, X_{2}$ and $X_{3}$ denote the amounts of these grades purchased (gallons) on a particular day. Suppose the $X_{i}^{\prime} s$ are independent with $\mu_{1}=1000, \mu_{2}=500$, $\mu_{3}=300, \sigma_{1}=100, \sigma_{2}=80$ and $\sigma_{3}=50$. The revenue from sales is $Y=2.2 X_{1}+2.35 X_{2}+2.5 X_{3}$.
(1) What is $E(Y)$ ?
(2) What is $V(Y)$ ?

## For general normal random variables

## Proposition 3

When $X_{1}, \ldots, X_{n}$ are independent and normally distributed, suppose $X_{i} \sim N\left(\mu_{i}, \sigma_{i}^{2}\right)$, then for any linear combination $Y=a_{1} X_{1}+\ldots+a_{n} X_{n}=\sum_{i=1}^{n} a_{i} X_{i}$,

$$
Y \sim N\left(\sum_{i=1}^{n} a_{i} \mu_{i}, \sum_{i=1}^{n} a_{i}^{2} \sigma_{i}^{2}\right)
$$

Remark. This proposition is true ONLY for Normal Random Variables.

## For iid normal random sample

Corollary
When $X_{1}, \ldots, X_{n}$ are i.i.d and $X_{i} \sim N\left(\mu, \sigma^{2}\right)$, then for any linear combination $Y=a_{1} X_{1}+\ldots+a_{n} X_{n}=\sum_{i=1}^{n} a_{i} X_{i}$,

$$
Y \sim N\left(\left(\sum_{i=1}^{n} a_{i}\right) \mu,\left(\sum_{i=1}^{n} a_{i}^{2}\right) \sigma^{2}\right) .
$$

## Introduce another tool to derive distribution

## Proposition 4

Let $X_{1}, X_{2}, \ldots, X_{n}$ independent random variables with mgfs $M_{X_{i}}(t)$ and $Y$ is the linear combination defined in equation (1), then

$$
\begin{equation*}
M_{Y}(t)=M_{X_{1}}\left(a_{1} t\right) \times M_{X_{2}}\left(a_{2} t\right) \times \ldots \times M_{X_{n}}\left(a_{n} t\right) \tag{2}
\end{equation*}
$$

## Normal case

$X$ and $Y$ are independent Normal random variable. $X$ has mean $\mu_{1}$ and variance $\sigma_{1}$. $Y$ has mean $\mu_{2}$ and variance $\sigma_{2}$. What's the distribution of $X+Y$ ?

## Poisson case

$X$ and $Y$ are independent Poisson random variable. $X$ has mean $\nu$ and $Y$ has mean $\lambda$. What's the distribution of $X+Y$ ? (Example 6.16 page 306 )

Homework for Section 6.3: 33, 34, 44.

## HW1

- Due next Jan. 18
- Hand-in: (Sec 6.1 P290) 2, 3 ; (Sec 6.3 P306) 33, 34, 44
- Not-Hand-in: Reading
(1) Book sections 6.1, 6.3
(2) [Reading 1] under Readings tag of course website.

