# STAT 516 <br> Lecture 8: Normal distribution 

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April 3, 2020

## Introduction

- Most empirical data that seem to be unimodal and not strongly skewed are commonly modeled using the normal distribution
- When a new methodology is presented, it is typically tested on the normal distribution first
- The best-known procedures in statistics have their exact inferential optimality properties when the data come from the normal distribution


## Definition

- $X \sim N\left(\mu, \sigma^{2}\right)$ when its pdf is

$$
f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{-\frac{(x-\mu)^{2}}{2 \sigma^{2}}}
$$

for any $-\infty<x<\infty$

- In this definition, $\mu$ can be any real number and $\sigma>0$.
- The case $X \sim N(0,1)$ is called a standard normal random variable


## Definition

- The density of the standard normal random variable is denoted as $\phi(x)$ and is

$$
\phi(x)=\frac{1}{\sqrt{2 \pi}} e^{-\frac{x^{2}}{2}}
$$

for any $-\infty<x<\infty$

- $\phi(x)$ is symmetric and unimodal about zero. The general $N\left(\mu, \sigma^{2}\right)$ is symmetric and unimodal around $\mu$


## Definition

- By definition, the CDF of the standard normal distribution is

$$
\Phi(x)=\int_{-\infty}^{x} \phi(z) d z
$$

- Due to the symmetry of the standard normal distribution around zero

$$
\Phi(-x)=1-\Phi(x)
$$

- The change of $\mu$ results in the shift of the distribution to the new center
- The increase of $\sigma^{2}$ results in the new distribution being more spread out


## Standard Normal CDF at Selected Values

| x | $\Phi(x)$ |
| :---: | :---: |
| -4 | 0.0003 |
| -3 | 0.00135 |
| -2 | 0.02275 |
| -1 | 0.15866 |
| 0 | 0.5 |
| 1 | 0.84134 |
| 2 | 0.97725 |
| 3 | 0.99865 |
| 4 | 0.99997 |

## Basic properties

- If $X \sim N\left(\mu, \sigma^{2}\right)$, then $Z=\frac{X-\mu}{\sigma} \sim N(0,1)$; if $Z \sim N(0,1)$, then $X=\mu+\sigma Z \sim N\left(\mu, \sigma^{2}\right)$
- If $X \sim N\left(\mu, \sigma^{2}\right)$, then

$$
P(X \leq x)=\Phi\left(\frac{x-\mu}{\sigma}\right)
$$

In particular, $P(X \leq \mu)=P(Z \leq 0)=0.5$ i.e. $\mu$ is the median of $X$

- Every moment of any normal distribution exists; for any $k$, $E\left[(X-\mu)^{2 k+1}\right]=0$


## Basic properties

- If $Z \sim N(0,1)$, then

$$
E\left(Z^{2 k}\right)=\frac{(2 k)!}{2^{k} k!}
$$

for any $k \geq 1$

- The MGF of $N\left(\mu, \sigma^{2}\right)$ exists for all real $t$ and is

$$
\psi(t)=e^{t \mu+\frac{t^{2} \sigma^{2}}{2}}
$$

## Corollary

- Let $X \sim N\left(\mu, \sigma^{2}\right)$ and $0<\alpha<1$.
- Let $Z \sim N(0,1)$ and denote $x_{\alpha}$ the $(1-\alpha)$ th quantile of $X$
- Finally, let $z_{\alpha}$ is the $(1-\alpha)$ th percentile of $Z$. Then,

$$
x_{\alpha}=\mu+\sigma z_{\alpha}
$$

## Basic Example I

- By using a standard normal CDF table, we can easily find 75th, 90th, 97.5th, 99th, and 99.5th percentiles of the standard normal distribution

| $\alpha$ | $1-\alpha$ | $z_{\alpha}$ |
| :---: | :---: | :---: |
| 0.25 | 0.75 | 0.675 |
| 0.1 | 0.9 | 1.282 |
| 0.05 | 0.95 | 1.645 |
| 0.025 | 0.975 | 1.960 |
| 0.01 | 0.99 | 2.326 |
| 0.005 | 0.995 | 2.576 |

## Basic Example II

- The age of the subscribers to a newspaper has a normal distribution with mean 50 years and standard deviation 5 years. Compare the percentage of subscribers who are less than 40 years old and the percentage who are between 40 and 60 years old.
- $X \sim N\left(\mu, \sigma^{2}\right)$ with $\mu=50$ and $\sigma=5$ is the age of a subscriber. Then,

$$
P(X<40)=\Phi\left(\frac{40-50}{5}\right)=\Phi(-2)=0.02275
$$

and

$$
\begin{aligned}
& P(40 \leq X \leq 60)=P(X \leq 60)-P(X \leq 40) \\
& =\Phi(2)-\Phi(-2)=0.9545
\end{aligned}
$$

## Example I

- Let $X$ denote the length of time (in minutes) an auto battery will continue to crank an engine. Assume that $X \sim N(10,4)$.
- What is the probability that the battery will crank the engine longer than $10+x$ minutes given that it is still cranking in 10 minutes?

$$
\begin{aligned}
& P(X>10+x \mid X>10)=\frac{P(X>10+x)}{P(X>10)}=\frac{P(Z>x / 2)}{1 / 2} \\
& =2\left[1-\Phi\left(\frac{x}{2}\right)\right]
\end{aligned}
$$

- Note that the resulting function is decreasing in $x$.
- This is different from the exponential distribution with the same mean $\mu=10$


## Example II

- Let the thermostat be set at $d$ degrees Celsius.
- The actual temperature of a certain room is $N\left(d, \sigma^{2}\right)$ with $\sigma=0.5$
- If the thermostat is set at 75 degrees, what is the probability that the actual temperature is below 74 degrees?
$P(X<74)=P(Z<(74-75) / 0.5)=P(Z<-2)=0.02275$


## Example II

- What is the lowest setting of the thermostat that will maintain a temperature of at least 72 degrees with probability of 0.99 ?
- We need to find the value of $d$ such that $P(X \geq 72)=0.99$, or equiv. $P(X<72)=0.01$
- Note that $P(Z<-2.36)=0.01$ (e.g. see the normal distribution table or use the software)
- Thus, need to find $d$ such that $d+\sigma(-2.326)=72$ which results in $d=73.16$ degrees


## Sums of independent normal variables

- Let $X_{1}, \ldots, X_{n}$ for $n \geq 2$ be independent random variables $X_{i} \sim N\left(\mu_{i}, \sigma_{i}^{2}\right)$.
- Also, let $S_{n}=\sum_{i=1}^{n} X_{i}$.
- Then,

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

- A sum of any number of independent normal random variables is exactly normally distributed
- Note that a more general statement is also true: for any set of constants $a_{1}, \ldots, a_{n}$

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

## Proof

- The mgf of $S_{n}$ is

$$
\begin{aligned}
& \psi_{S_{n}}(t)=E\left(e^{t S_{n}}\right)=E\left(e^{t X_{1}} \cdots e^{t X_{n}}\right)=\prod_{i=1}^{n} E\left(e^{t X_{i}}\right) \\
& =\prod_{i=1}^{n} e^{t \mu_{i}+t^{2} \sigma_{i}^{2} / 2}=e^{t\left(\sum_{i=1}^{n} \mu_{i}\right)+\left(t^{2} / 2\right)\left(\sum_{i=1}^{n} \sigma_{i}^{2}\right)}
\end{aligned}
$$

- The last expression is the mgf of $N\left(\sum_{i=1}^{n} \mu_{i}, \sum_{i=1}^{n} \sigma_{i}^{2}\right)$


## Corollary

- Suppose $X_{i}, 1 \leq i \leq n$ are independent and each is distributed as $N\left(\mu, \sigma^{2}\right)$.
- Then, $\bar{X}=\frac{S_{n}}{n} \sim N\left(\mu, \frac{\sigma^{2}}{n}\right)$.
- Thus, the distribution of $\bar{X}$ becomes more concentrated around the true mean $\mu$ as the sample size grows.
- Therefore, $\bar{X}$ becomes better and better as an estimator of $\mu$.


## Example I

- Suppose $X \sim N(-1,4), Y \sim N(1,5)$ and they are independent.
- What is the CDF of $X+Y$ and $X-Y$ ?
- First, $X+Y \sim N(0,9)$ and $X-Y \sim N(-2,9)$
- Therefore, $P(X+Y \leq x)=\Phi\left(\frac{x}{3}\right)$ and $P(X-Y \leq x)=\Phi\left(\frac{x+2}{3}\right)$


## Example II

- Let $X_{1}, \ldots, X_{n} \sim N\left(\mu, \sigma^{2}\right)$ are independent (they are iid)
- Therefore, $\bar{X} \sim N\left(\mu, \sigma^{2} / n\right)$ and

$$
\begin{aligned}
& P(\bar{X}-1.96 \sigma / \sqrt{n} \leq \mu \leq \bar{X}-1.96 \sigma / \sqrt{n}) \\
& =P(-1.96 \sigma / \sqrt{n} \leq \bar{X}-\mu \leq 1.96 \sigma / \sqrt{n}) \\
& =P\left(-1.96 \leq \frac{\bar{X}-\mu}{\sigma / \sqrt{n}} \leq 1.96\right)=\Phi(1.96)-\Phi(-1.96)=0.95
\end{aligned}
$$

- Thus, with probability $95 \%$ for any $n$ we have that the true mean $\mu$ is between $\bar{X}-1.96 \sigma / \sqrt{n}$ and $\bar{X}+1.96 \sigma / \sqrt{n}$
- We obtained a simple $95 \%$ confidence interval for $\mu$ with the margin of error $1.96 \sigma / \sqrt{n}$.

