This work is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike License. Your use of this material constitutes acceptance of that license and the conditions of use of materials on this site.


Copyright 2009, The Johns Hopkins University and John McGready. All rights reserved. Use of these materials permitted only in accordance with license rights granted. Materials provided "AS IS"; no representations or warranties provided. User assumes all responsibility for use, and all liability related thereto, and must independently review all materials for accuracy and efficacy. May contain materials owned by others. User is responsible for obtaining permissions for use from third parties as needed.

JOHNS HOPKINS BLOOMBERG SCHOOL of PUBLIC HEALTH

Describing Data: Part II

John McGready Johns Hopkins University

## Lecture Topics

- The normal distribution
- Means, variability, and the normal distribution
- Calculating normal (z) scores
- Means, variability and z-scores for non-normal distributions


## Section A

The Normal Distribution

## The Normal Distribution

- The normal distribution is a theoretical probability distribution that is perfectly symmetric about its mean (and median and mode), and had a "bell" like shape



## The Normal Distribution

- The normal distribution is also called the "Gaussian distribution" in honor of its inventor Carl Friedrich Gauss



## The Normal Distribution

- Normal distributions are uniquely defined by two quantities: a mean $(\mu)$, and standard deviation ( $\sigma$ )
- There are literally an infinite number of possible normal curves, for every possible combination of $(\mu)$ and $(\sigma)$



## The Normal Distribution

- Normal distributions are uniquely defined by two quantities: a mean $(\mu)$, and standard deviation ( $\sigma$ )
- There are literally an infinite number of possible normal curves, for every possible combination of $(\mu)$ and $(\sigma)$



## The Normal Distribution

- Normal distributions are uniquely defined by two quantities: a mean $(\mu)$, and standard deviation ( $\sigma$ )
- There are literally an infinite number of possible normal curves, for every possible combination of $(\mu)$ and $(\sigma)$
- This function defines the normal curve for any given $(\mu)$ and ( $\sigma$ )

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

## Normal Distribution

- Areas under a normal curve represent the proportion of total values described by the curve that fall in that range



## Normal Distribution

- This shaded area represents the proportion of values (observations) between 0 and 1 following a normal distribution with $\mu=0$ and $\sigma=1$
- The shaded area is approximately $29 \%$ of the total area under the curve



## Normal Distribution

- The normal distribution is a theoretical distribution: no real data will truly be normally distributed (at the sample or population level)
- For example: the tails of the normal curve are "infinite"



## Normal Distribution

- BUT: some data approximates a normal curve pretty well
- Here is a histogram of the BP of the 113 men with a normal curve superimposed (normal curve has same mean and SD as sample of 113 men)
- Mean 123.6 mmHG, SD 12.9 mmHg



## Normal Distribution

- Other data, does not approximate a normal distribution
- Here is a histogram of the hospital length of stay of the 500 patients with a normal curve superimposed (normal curve has same mean and SD as sample of 500 patients)
- Mean 5.1 days, SD 6.4 days



## Section B

Variability in the Normal Distribution: Calculating Normal Scores

## The Standard Normal Distribution

- The standard normal distribution has a mean of 0 , and standard deviation of 1



## The 68-95-99.7 Rule for the Normal Distribution

- $68 \%$ of the observations fall within one standard deviation of the mean



## The 68-95-99.7 Rule for the Normal Distribution

- $95 \%$ of the observations fall within two standard deviations of the mean (truthfully, within 1.96)



## The 68-95-99.7 Rule for the Normal Distribution

■ $99.7 \%$ of the observations fall within three standard deviations of the mean


## Fraction of Observations under Standard Normal

|  | Within Z SDs of <br> the mean | More than Z <br> SDs above the <br> mean |
| :--- | :--- | :--- |
| Z | More than <br> Z SDs above <br> or below the <br> mean |  |
|  |  |  |
| 1.0 | $68.27 \%$ | $15.87 \%$ |

## Fraction of Observations under Standard Normal

|  | Within Z SDs of <br> the mean | More than Z <br> SDs above the <br> mean |
| :--- | :--- | :--- |
| Z | More than <br> Z SDs above <br> or below the <br> mean |  |
| 1.0 | $68.27 \%$ | $15.87 \%$ |

## Fraction of Observations under Standard Normal

|  | Within Z SDs of <br> the mean | More than Z <br> SDs above the <br> mean | More than <br> Z SDs above <br> or below the <br> mean |
| :--- | :--- | :--- | :--- |
| Z |  |  |  |
| 1.0 | $68.27 \%$ | $15.87 \%$ | $31.73 \%$ |
| 2.0 | $95.45 \%$ | $2.28 \%$ | $4.55 \%$ |
| 2.5 | $98.76 \%$ | $0.62 \%$ | $1.24 \%$ |
| 3.0 | $99.73 \%$ | $0.13 \%$ | $0.27 \%$ |

## The 68-95-99.7 Rule for the Normal Distribution

- What about other normal distributions with other means and standard deviations?
- Same exact properties apply
- In fact, any normal distribution with any mean and standard deviation can be transformed to a standard normal curve


## Transforming to Standard Normal

- The standard normal curve (blue) and another normal with mean -2 , and standard deviation 2



## Transforming to Standard Normal

- To center at zero, subtract of mean of -2 from each observation under the red curve



## Transforming to Standard Normal

- To "change shape" (i.e., change spread; i.e., standard deviation) divide each "new observation" by standard deviation of 2



## Transforming to Standard Normal

- To "change shape" (i.e., change spread; i.e., standard deviation) divide each "new observation" by standard deviation of 2



## Transforming to Standard Normal

- This process is called standardizing or computing z -scores
- A z-score can be computed for any observation from any normal curve
- A z-score measures the distance of any observation from its distribution's mean in units of standard deviation
- This $z$-score can help asses where the observations fall relative to the rest of the observations in the distribution
- z-score computed by: $z=\frac{\text { observation - mean }}{\text { standard deviation }}$


## Example 1: Blood Pressure in Males

- Histogram of BP values for random sample of 113 men suggest BP measurements approximated by a normal distribution



## Example 1: Blood Pressure in Males

- Data in Stata

```
. list bp in 1/10
    +-------+
    | bp |
    |-------- |
1. | 89 |
2. | 99 |
3. | 101 |
4. | 101 |
5. | 103 |
    |-------- |
    6. | 103 |
7. | 104 |
8. | 105 |
9. | 106 |
10. | 106 |
    +--------
```


## Example 1: Blood Pressure in Males

- Summarize command gives sample mean and standard deviation

```
. summarize bp
    Variable |
                            Obs
                                Mean
                                Std. Dev.
                                Min
                                Max
        bp |
            1 1 3
                    123.5929
                        12.86512
                            89
                            1 5 2
```


## Example 1: Blood Pressure in Males

- Summarize command gives sample mean and standard deviation (and sample size, minimum and maximum values)

```
. summarize bp
    Variable | Obs Mean Std. Dev. Min Max
        llllllll
    \overline{x}=123.6 mmHg; s=12.9 mmHg
```


## Example 1: Blood Pressure in Males

- Using the sample data, let's estimate the range of blood pressure values for "most" (95\%) of men in the population
- For normally distributed data, $95 \%$ will fall within 2 sds of the mean

$$
\begin{aligned}
& \bar{x} \pm 2 s \\
& 123.6 \pm 2 \times 12.9 \\
& (97.8,149.4)
\end{aligned}
$$

- Again, this is just an estimate using the best guesses from the sample for mean and sd of the population


## Example 1: Blood Pressure in Males

- Suppose a man comes into my clinic, gets his blood pressure measured, and wants to know how he compares to all men
- His blood pressure is 130 mmHg
- What percentage of men have blood pressures greater than 130 mmHg ?
- Translate to z-score $z=\frac{130-123.6}{12.9} \approx 0.5$
- Question akin to "what percentage of observations under a standard normal curve are 0.5 sds or more above the mean in value?"


## Example 1: Blood Pressure in Males

- Could look this up in a normal table (more extensive tables can be found in the back of any stats book or by searching online)
- Could also use normal function in Stata


## Example 1: Blood Pressure in Males

- Typing display normal(z) at command line gives proportion of observation less than z standard deviations from mean:



## Example 1: Blood Pressure in Males

- For $z=0.5$, roughly $69 \%$ percent of observations fall below .5 sds from mean
. display normal(.5)
.69146246



## Example 1: Blood Pressure in Males

- For $z=0.5$, roughly $100 \%-69 \%=31 \%$ of observations fall above .5 sds from mean
- display $1+$ normal(.5)
.30 .05754



## Example 1: Blood Pressure in Males

- So approximately $31 \%$ of all men have blood pressures greater than our subject with a blood pressure of 130
- What percentage of men have blood pressures more extreme, i.e. farther than .5 sds from the mean of all men in either direction?


## Example 1: Blood Pressure in Males

- What we want



## Example 1: Blood Pressure in Males

- By symmetry of normal curve, $31 \%$ of observations are above .5 sd , and $31 \%$ below -. 5 sd
- So a total of $62 \%$ is farther than .5 sds from mean in either direction



## Section C

Normal Scores and Variability in Non-Normal Data

## Why Do We Like The Normal Distribution So Much?

- The truth is, there is nothing "special" about standard normal scores
- These can be computed for observations from any sample/ population of continuous data values
- The score measures how far an observation is from its mean in standard units of statistical distance


## Why Do We Like The Normal Distribution So Much?

- However, unless population/sample has a well known, "well behaved" (like a normal) distribution, we may not be able to use mean and standard deviation to create interpretable intervals, or measure "unusuality" of individual observations


## Hospital Length of Stay Example

- Random sample of 500 patients
- Mean length of stay: 4.8 days
- Median length of stay: 3 days
- Standard deviation: 6.3 days
- Data in Stata
list hospstay in $1 / 10$



## Hospital Length of Stay Example

- Random sample of 500 patients
- Mean length of stay: 4.8 days
- Median length of stay: 3 days
- Standard deviation: 6.3days



## Hospital Length of Stay Example

- Summarize command with detail option

| summarize hospstay, detail |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| hospstay |  |  |  |  |
|  | Percentiles | Smallest |  |  |
| 1\% | 1 | 1 |  |  |
| 5\% | 1 | 1 |  |  |
| 10\% | 1 | 1 | Obs | 500 |
| 25\% | 1 | 1 | Sum of Wgt. | 500 |
| 50\% | 3 |  | Mean | 4.808 |
|  |  | Largest | Std. Dev. | 6.282521 |
| 75\% | 5 | 37 |  |  |
| 90\% | 11 | 37 | Variance | 39.47008 |
| 95\% | 17 | 39 | Skewness | 3.622325 |
| 99\% | 35 | 60 | Kurtosis | 21.68121 |

## Hospital Length of Stay Example

- Summarize command with detail option

|  | hospstay |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Percentiles | Smallest |  |  |
| 1\% | 1 | 1 |  |  |
| 5\% | 1 | 1 |  |  |
| 10\% | 1 | 1 | Obs | 500 |
| 25\% | 1 | 1 | Sum of Wgt. | 500 |
| 50\% | 3 |  | Mean | 4.808 |
|  |  | Largest | Std. Dev. | 6.282521 |
| 75\% | 5 | 37 |  |  |
| 90\% | 11 | 37 | Variance | 39.47008 |
| 95\% | 17 | 39 | Skewness | 3.622325 |
| 99\% | 35 | 60 | Kurtosis | 21.68121 |

## Hospital Length of Stay Example

- Histogram of sample data



## Constructing Intervals

- Suppose I wanted to estimate an interval containing roughly $95 \%$ of the values of hospital length of stay in the population
- Distribution right skewed-can not appeal to properties/methods of normal distribution!
- Mean $\pm 2$ SDs
$-4.8 \pm 2 \times 6.3$
- This gives an interval from -7.8 to 17.4 days!


## Hospital Length of Stay Example

- Histogram of sample data



## Constructing Intervals

- We would need to estimate this interval from the histogram and/or by finding sample percentiles



## Constructing Intervals

- Using percentiles
- Syntax "centile varname, c(\#1, \#2, . . .)"
. centile hospstay, c(2.5,97.5)

| Variable | Obs | Percentile | Centile | ```-- Binom. Interp. -- [ 95% Conf. Interval]``` |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| hospstay | 500 | 2.5 | 1 | 1 | 1 |
|  |  | 97.5 | 23.475 | 17.69772 | 32.67554 |

## Constructing Intervals

- Using percentiles
- Syntax "centile varname, c(\#1, \#2, . . .)"

```
centile hospstay, c(2.5,97.5)
```



- So based on this sample data we estimate that $95 \%$ of discharged patients had length of stay between 1 and 24 days


## Constructing Intervals

- What percentage of patients had length of stay greater than five days?
- (Wrong approach) $z$-score $z=\frac{5-4.8}{6.4}=0.03$
- Assuming normality, this would suggest that nearly $50 \%$ of the patients had length of stay greater than five days


## Hospital Length of Stay Example

- According to percentiles, five days is the 75th percentile: so only $25 \%$ of the sample have length of stay over 5 days
summarize hospstay, detail

|  | Percentiles | Smallest |  |  |
| :---: | :---: | :---: | :---: | :---: |
| 1\% | 1 | 1 |  |  |
| 5\% | 1 | 1 |  |  |
| 10\% | 1 | 1 | Obs | 500 |
| 25\% | 1 | 1 | Sum of Wgt. | 500 |
| 50\% | 3 |  | Mean | 4.808 |
|  |  | Largest | Std. Dev. | 6.282521 |
| 75\% | 5 | 37 |  |  |
| 90\% | 11 | 37 | Variance | 39.47008 |
| 95\% | 17 | 39 | Skewness | 3.622325 |
| 99\% | 35 | 60 | Kurtosis | 21.68121 |

