Module 3: Describing Data

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Introduction to Statistics for the Social Sciences

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Outline

1. Introduction
   - Context of example data
   - Descriptive Statistics
   - Notation
   - Summation

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   - Descriptive Statistics
   - Notation
   - Summation
2. Classes of Descriptive Statistics
   - Central Tendency
   - Dispersion
   - Shape
   - Relationship

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How will Bob **describe** his data?

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Describing Data

Bob is interested in describing the extraction and cost of his rigs. But, he does not want to look at all 1000 rigs' data (*population*) and instead decides to draw at random 10 rigs' data (*sample*) which is available on the next slide (Table 1).

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- Descriptive Statistics only allow us to *describe* the data.

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Data: Extraction & Cost Sample (n = 10)

Table 1: Raw Data for One Month

rig	barrels	costs
065	166	570
142	185	560
198	159	520
277	207	580
408	194	530
533	191	560
621	176	510
788	216	550
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“rig” = identification number; “barrels” = 1,000 barrels extracted; “costs” = 1,000 USD

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  - Which indicates that score 51 is located in the 2nd row and in the 3rd column of a table of data.

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- Each class tells Bob something about how his rigs are producing.
- Each class of Descriptive Statistics tells us something about how scores are distributed.

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  - One number which represents or characterizes the entire distribution (as best as one number can).
- Keep in mind, the center point of scores in a distribution may not be in the middle of the scale of those scores (more on this later).

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The mode is the most frequently occurring score in a distribution.

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- Con: Different samples almost always produce different modes for the same variable.

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Oil Sample (n = 10) Example showing the Mode

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Barrels:
Since no score on this variable occurs more than once, there are multiple modes. Meaning, all of the scores are the Mode.

Costs:
Since this is a very small data set (only 10 cases) and 560 is the only score which occurs more than once, it is very easy to identify it as the Mode.

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  - For an even number of scores, the average of the two middle scores is the median.

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Oil Sample (n = 10) Example showing the Median

Table 2: Sorted Sample Data

barrels	costs
159	510
166	520
176	530
185	550
191	560
194	560
199	560
207	560
216	570
228	580

Barrels: $Mdn = 192.5$
Costs: $Mdn = 560$

With an even number of scores, we must take the midpoint of the middle two scores.

Barrels: 191, 194

Costs: 560, 560

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$$\overline{X} = \frac{\sum X}{n}$$

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Oil Sample (n = 10) Example showing the Mean

General formula for Mean:

[2] Recall, the capital letter we chose to represent a variable is arbitrary, X and Y are commonly used examples.

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Costs: $\overline{Y} = \frac{510+520+530+550+560+560+560+560+570+580}{10}$

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- Costs: $\overline{Y} = \frac{5500}{10} = 550$

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  - Common examples are 10% and 20% trimmed means; where the 10 or 20% of the most extreme scores (high & low) are trimmed.

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- Trimmed mean simply refers to a mean calculated after "trimming" a certain percentage of extreme scores.
    - The median is an extreme example of a trimmed mean; the median trims all but the middle score or middle two scores.
    - Common examples are 10% and 20% trimmed means; where the 10 or 20% of the most extreme scores (high & low) are trimmed.
- M-estimators are weighted means; meaning scores near the middle are given more weight and scores at the extremes are given less weight.

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  - If our scores are: (5, 5, 5, 5, 5) then dispersion is zero and this is a constant.

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- Also note: when referring to total number of scores in a *population* we use N, in a *sample* we use n.

Standard Deviation: sample symbol = S, population symbol = σ

The Standard Deviation is the square root of the variance and allows us to compare the dispersion of one distribution to another.

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  - Sample Formula: $S = \sqrt{S^2}$
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- Note the use of the word “Standard” which you will see often; it refers to standardization, which tends to allow us to compare statistics from different variables or distributions (i.e., apples & oranges).

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- Either can be used; both types provide the same answer.

Calculating *SoS* using example data (X = barrels)

X_i	X	$\overline{X}$	$\left(X - \overline{X}\right)$	$\left(X - \overline{X}\right)^2$
1	159	192.1	-33.1	1095.61
2	166	192.1	-26.1	681.21
3	176	192.1	-16.1	259.21
4	185	192.1	-7.1	50.41
5	191	192.1	-1.1	1.21
6	194	192.1	1.9	3.61
7	199	192.1	6.9	47.61
8	207	192.1	14.9	222.01
9	216	192.1	23.9	571.21
10	228	192.1	35.9	1288.81
	$\sum X = 1921$	$SoS =$	$\sum \left(X - \overline{X}\right)^2$	$= 4220.90$

Sample mean $= \overline{X} = \sum X / n = 1921/10 = 192.1$

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- Sample Standard Deviation for 'Barrels' is:

$$S = \sqrt{\frac{\sum (X - \overline{X})^2}{n-1}} = \sqrt{\frac{SoS}{n-1}} = \sqrt{S^2} = \sqrt{468.99} = 21.66$$

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- You should be able to work backwards from the information in the lines directly above to get the standard deviation, variance, & sums of squares for 'Costs'.

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The farther from zero the skewness, the less symmetric the distribution of scores.

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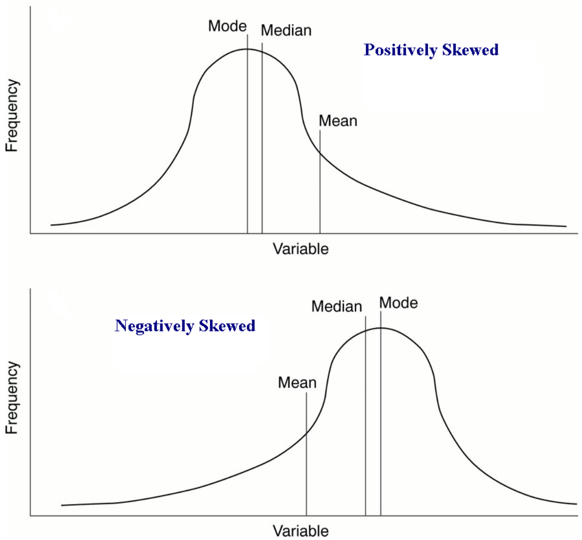
Recognizing Skewness



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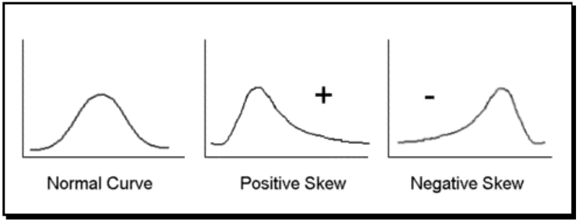
Recognizing Skewness

Zero Skewness Positive Skewness Negative Skewness



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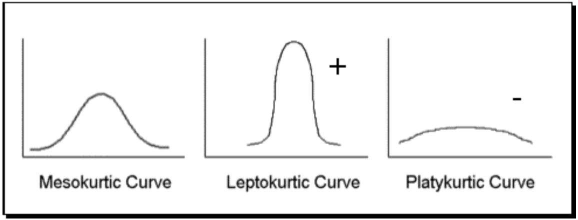
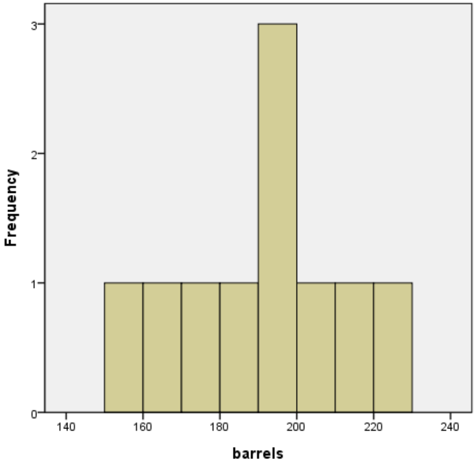


Describing a Distribution’s Shape

How can we describe the shape of the distribution of our sample’s Barrels variable?



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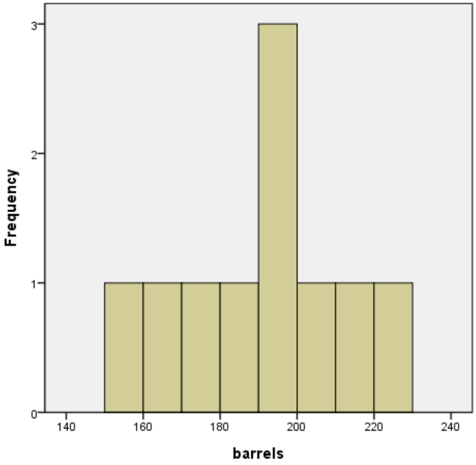

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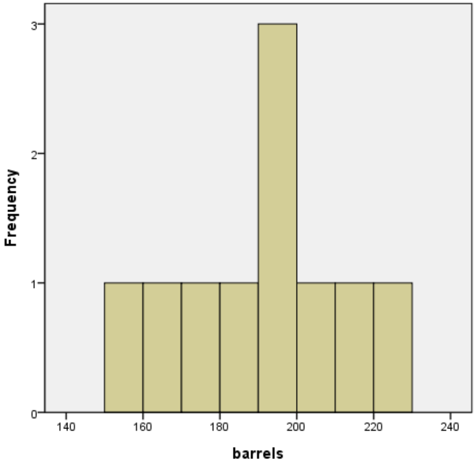

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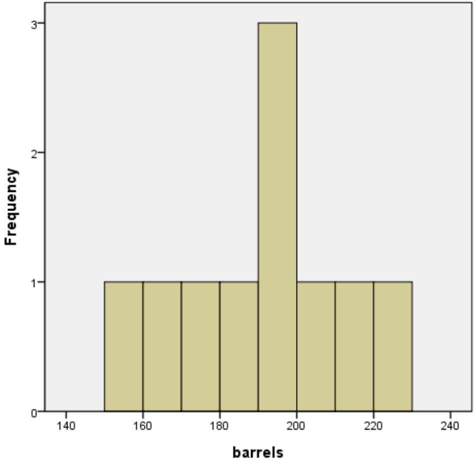

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- When a variable displays a skewness or kurtosis larger than +1 or -1, then we say the variable is not symmetrical and/or does not have well proportioned tails.

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Relationship

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- Phi Coefficient (ϕ) when both variables are dichotomous.
- Spearman's rho (ρ) or (r_s) and Kendall's tau (τ) when one or both variables are ranked (ordinal).

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The definitional formula for calculating the covariance of two *sample* variables (X, Y) is:

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Oil Example sample data: Covariance Calculation

XY_i	Barrels (X)	Costs (Y)	XY
1	159	520	82680
2	166	570	94620
3	176	510	89760
4	185	560	103600
5	191	560	106960
6	194	530	102820
7	199	560	111440
8	207	580	120060
9	216	550	118800
10	228	560	127680
	$\sum X = 1921$	$\sum Y = 5500$	$\sum XY = 1058420$

$$n = 10$$

Example Calculation continued

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- Positive number, indicates that high scores on X are associated with high scores on Y (and vice versa).
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- Beyond that, not much can be said.

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The Correlation (r) is a standardized measure of relationship; meaning it can be compared across multiple pairs of variables, regardless of scale.

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- Correlation is used in many inferential statistics and often a matrix of correlations is the input data used to calculate them.

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The size of r indicates the *strength* of the relationship and the sign (positive or negative) indicates the *direction* of the relationship.

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  - In the social sciences, it is common to find correlations around .400 to .600 referred to as ‘moderate’, ‘good’, or even ‘strong’ (in the case of .600).

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  - Squaring any correlation coefficient makes it smaller (r is always between -1 and +1).

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- Our correlation shrank from $r = .424$ to $r_{adj} = .278$
- Shared variance shrank from $r^2 = .1789$ to $r^2_{adj} = .0773$.
- We now have a *more* accurate sample estimate of the relationship between Barrels and Costs.

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Adjusting our Oil example correlation:

$$r_{adj} = \sqrt{1 - \frac{(1-r^2)(n-1)}{n-2}} = \sqrt{1 - \frac{(1-.424^2)(10-1)}{10-2}} = \ldots$$

$$\sqrt{1 - \frac{(1-.1798)(9)}{8}} = \sqrt{1 - \frac{(.8202)(9)}{8}} = \ldots$$

$$\sqrt{1 - \frac{7.3818}{8}} = \sqrt{1 - .9227} = \ldots$$

$$\sqrt{.0773} = .2780$$

- Our correlation shrank from $r = .424$ to $r_{adj} = .278$
- Shared variance shrank from $r^2 = .1789$ to $r^2_{adj} = .0773$.
- We now have a *more* accurate sample estimate of the relationship between Barrels and Costs.
- They share 7.73% of their variance (i.e., clearly a weak relationship).

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Additional Considerations with Measures of Relationship

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- You will often hear this: “Correlation does **not** equal causation!”
  - X may cause Y
  - Y may cause X
  - Z may be causing the relationship between X and Y
- Although, we do tend to use correlation (and other measures of relationship) in the process of *investigating* causal relationships.

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Properties of Statistics

There are 4 properties we use to evaluate statistics.

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Some of them you are already familiar with...

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- As an example, consider measures of central tendency:
  - The mean is very *sufficient* because, it uses all the scores when being calculated.
  - The median and mode are not very sufficient because, they only use one or two scores.

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- When dealing with samples, we do not have all the scores (of the defined population) and we make an adjustment, dividing by $n - 1$.

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- The key to that statement being true is "symmetrical population distribution with μ in the center".
  - Extremely high and low scores (those farthest from μ) are rare when compared to the number of scores near μ.
  - Therefore, we can expect most of those repeated samples to have a mean close to μ, because most of the scores in general (in the population) are close to μ.

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- If extreme scores do **not** influence the statistic, then the statistic is *resistant*.
- Again, consider measures of central tendency: Mo, Mdn, $\overline{X}$
- Both Mo and Mdn only consider the very center of a distribution, so they are very *resistant*.
- $\overline{X}$ is very sensitive to outliers, they *pull* the mean toward them thus making the mean not very resistant.

Summary of Module 3 (continued on next slide)

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Summary continued

- Classes of Descriptive Statistics (continued)

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This concludes Module 3

Next time Module 4.

- Next time we'll begin covering "The Normal Curve".
- Until next time; have a nice day.

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