Part I	Exploring and Understanding Data
Chapter 1	Stats Starts Here
Statistics is	a way of reasoning, along with a collection of tools and methods,
	designed to help us understand the world.
Statistics are	particular calculations made from data.
A statistic is	A numerical summary of data
Statistics is about	variation
Chapter 2	Data
Data are	values along with their context
The context for data values is	The "W's"
provided by	Why do we care about the data?
	Who are the individuals described by the data?
	What variables do the data contain?
	When
	Where
	How
	(Necessary)
Three steps to doing Statistics	Think –were you're headed and why (the "W's").
right:	Show – the mechanics of calculating statistics and making displays.
	Tell – what you've learned remembering the "4 Cs."
4 Cs: conclusions are	Clear, concise, complete, and in context.
Data table	An arrangement of data in which each row represents a case and
	each column represents a variable.
Case	An individual about whom we have data (row of data table)
Individual	Object described by a set of data (person, animal, thing, identifier
	variable)
Variable	Holds information about the same characteristic for many cases.
	(column of data table)
Variables can usually be	
identified as either or:	Categorical or quantitative
Categorical variable	Places an individual into one of several groups or categories
Quantitative variable	Has numerical values (with units) that measure some characteristic
	of each individual.
Ordinal variable	Reports order with out natural units.
You must look at the	Why
of your study to decide whether	
to treat it as or	Categorical or quantitative
Identifier variable	ID number or other convention often used to protect confidentiality
	(Categorical variable with exactly one individual in each category)
Chapter 3	Displaying and Describing Categorical Data
Three things you should always	1. Make a picture – a display will help you <i>think</i> clearly about
do first with data:	patterns and relationships that may be hiding in your data.
	2. Make a picture – <i>show</i> important features and patterns in your
	data
	3. Make a picture – best way to <i>tell</i> others about your data.
To analyze categorical data, we	
often use or	counts (frequencies) or percents (relative frequencies)

of individuals that fall into	
various categories.	
(Relative) Frequency table	Lists the categories in a categorical variable and the (percentage)
[Distribution of a categorical	count of observations for each category.
variable]	
Area principle	In a statistical display, each data value should be represented by the
	same amount of area.
(Relative Frequency) Bar chart	Shows a bar representing the (percentage) count of each category in
	a categorical variable.
Pie chart	Shows how a "whole" divides into categories by showing a wedge
	of a circle whose area corresponds to the proportion in each
	category.
Contingency table	Displays counts (percentages) of individuals falling into named
	categories on two (or more) variables, columns vs. rows. The table
	categorizes the individuals on all variables at once, to reveal
	possible patterns in one variable that may be contingent on the
	category of the other.
Marginal distribution	The distribution of one of the variables <u>alone</u> is seen in the totals
	found in the last row/column of a contingency table. (see frequency
	table)
Conditional distribution	The distribution of a variable restricting the <i>Who</i> to consider only a
	smaller group of individuals.
	[A single row (column) of the contingency table.]
Relationships among	
categorical variables are	
described by calculating	percents
from the given. This	counts
avoids	count variation between them.
Segmented Bar Chart	A stacked relative frequency bar chart (100% total).
	Often better than a pie chart for comparing distributions.
	[a pie chart within a bar chart]
Independent variables	The conditional distribution of one variable is the same for each
	category of the other.
	[if rows (columns) of contingency table have = distributions]
Simpson's paradox	When averages are taken across different groups, they can appear to
	contradict the overall averages
Chapter 4	Displaying Quantitative Data
Distribution of a quantitative	Tells us what values a variable takes and how often it takes them.
variable	Shows the pattern of variation of a (quantitative) variable.
Stem-and-leaf plot	A sideways histogram that shows the individual values.
	Bins/intervals might be the tens places with the ones places strung
	out sequentially to the right.
Back-to-back stem-and-leaf plot	Useful for comparing two related distributions with a moderate
	number of observations.
Dotplot	Graphs a dot for each case against a single axis.
(Relative Frequency) Histogram	Uses adjacent, equal-width bars to show the distribution of values in
	a quantitative variable. Each bar represents the (percentage) count
	falling in a particular interval of values. (% are useful for comparing

	several distributions with different numbers of observations.)
A good estimate for how many	
bars will give a decent	Number of observations
histogram =	5
Once we make a picture, we	Shape, center, spread, and any unusual features.
describe a distribution by telling	
about its	
Shape	Uniform, single, multiple modes
	Symmetry vs. skewed
Uniform	A distribution that is roughly flat.
Mode	A hump or local high point in the shape of the distribution of a
	variable (unimodal, bimodal, multimodal).
Symmetric	A distribution where the two halves on either side of the center look
	approximately like mirror images of each other.
Skewed (left/right)	A non-symmetrical distribution where one tail stretches out further
	(to the left/right) than the other.
Center	A "typical" value that attempts the impossible, summarizing the
	entire distribution with a single number. {midpoint}
Spread	A numerical summary of how tightly the values are clustered around
	the "center." {range}
Outliers	Extreme values that don't appear to belong with the rest of the data.
Timeplot	Displays quantitative data collected over time (x-axis). Can reveal
-	trends overlooked by histograms and stem-and-leaf plots that ignore
	time order. Often, successive values are connected with lines to
	show trends more clearly.
Time series	Measurements of a variable taken at regular time intervals.
Seasonal variation	A pattern in a time series that repeats itself at know regular intervals
	of time.
Chapter 5	Describing Distributions Numerically
Median	Middle value (balances data by counts) (equal-areas point)
Range	Max – min data values
<i>p</i> th percentile	Value such that <i>p</i> percent of the observations fall at or below it.
Lower quartile (Q1)	Median of the lower half. (25 <sup>th</sup> percentile)
Upper quartile (Q3)	Median of the upper half. (75 <sup>th</sup> percentile)
Interquartile range (IQR)	Q3 - Q1, the middle half of the data.
5-number summary	Max
	Q3
	Median
	Q1
	Min
Suspected outlier	If observation $>$ Q3 + (1.5)(IQR)
_	Or observation $< Q1 - (1.5)(IQR)$
Boxplot	Displays the 5-number summary as a central box with whiskers that
	extend to the non-outlying data values. Particularly effective for
	comparing groups. However, a histogram or stem-and-leaf plot is a
	clearer display of the shape of a distribution.
Mean	[Average]

	$\overline{x} = \underline{\sum x}$
	Add up all the numbers and divide by n (balance point, by size) (balances deviations)
Deviation	How far each data value is from the mean
Variance	$\frac{\sum (r - \overline{r})^2}{r}$
	$s^2 = \frac{\sum (x - x)}{x - 1}$
	n-1 Sum of the squared deviations from the mean divided by $n = 1$
Standard deviation	Sum of the squared deviations from the mean, divided by $n = 1$ .
	$s = \sqrt{\frac{\sum (x-x)^2}{n-1}}$
	The square root of the variance (gets us back to the original units)
Report summary statistics to	
decimal places	1 or 2
	more than the original data.
When describing the	
distribution of a quantitative	
variable, if the shape is skewed	and top (the second secon
If the share is symmetric then	median and IQR (they are based on position)
report and	mean and standard deviation (they are based on size/value)
repeat calculations without	mean and standard deviation (they are based on size, value)
if present.	outliers
A complete analysis of data	
almost always includes:	Verbal, visual, and numerical summaries.
Answers are, not	sentences, numbers
Chapter 6	The Standard Deviation as a Ruler and the Normal Model
Adding (subtracting) a constant	
to every data value	adds (subtracts)
the same constant to measures	
of position/center and	daag wat shanga
Ineasures of spread.	does not change
data value by a constant	
the same constant	multiplies (divides)
to measures of position/center	
and measures of	multiplies (divides)
spread.	
Changing the center and spread	
of a variable is equivalent to	changing its units.
Standardizing	Uses the standard deviation as a ruler to measure distance from the
	mean creating z-scores
	$z = \frac{(x-x)}{x-x}$
	S
z-scores tell us	the number of standard deviations a value is from the mean.
important uses are:	<ul><li>the number of standard deviations a value is from the mean.</li><li>1. Comparing values from different distributions (decathlon events)</li></ul>

	2. Identifying unusual or surprising values among data.
	3.
Units can be eliminated by	standardizing the data
have no units	7-scores
When we standardize data to get	
when we standardize data to get we do two things	7-SCOPES
First we the data by	shift
subtracting the mean. Then we	Sint
the data by dividing by	rescale
their standard deviation	lescale
Standardizing has the following	Shana is not changed
affact on the distribution of a	Contor the mean is shifted to 0
veriable:	Spread the standard deviation is recealed to 1
Variable:	Spread – the standard deviation is rescaled to 1
If the distribution of a	
quantitative variable is	unimodal
and then the we can	roughly symmetric
replace histograms by	
approximating the distribution	
with	a normal model.
are summaries of	Statistics
the data denoted with	Latin letters
mean, standard deviation,	<i>x</i> , s
are numerically	Parameters
valued attributes [statistics] of a	
model (they don't come from	
the data, they just specify the	
model) denoted with	Greek letters
mean, standard deviation,	$\mu, \sigma$
A normal model is constructed	$1 - \frac{1}{2}(\frac{x-\mu}{x})^2$
from a rather complex equation	$y = \frac{1}{\sigma \sqrt{2\pi}} e^{-2\sigma}$
only dependent on parameters	$0\sqrt{2}\lambda$
for and	N(u, -)
	$N(\mu,\sigma)$
The distribution of each normal	
model is,, and	unimodal, symmetric, and bell-shaped
as show by its density curve.	
We call it a density curve	
because the equation for the	
normal model adjusts the scale	
(of y, height) so that the area	
under the curve = and gives	1
the for the distribution.	relative frequency
This scaling is extremely	Specifically, it allows us to convert standard deviations into percents
important in conceptualizing	that are much easier to comprehend.
how unusual a value(z-score) is.	L T
To avoid having to work with	we convert our data to z-scores and use just one Standard Normal
the complicated normal model	Model $N(0,1)$ and its associated table.
We call it a density curve because the equation for the normal model adjusts the scale (of y, height) so that the area under the curve = and gives the for the distribution. This scaling is extremely important in conceptualizing how unusual a value(z-score) is. To avoid having to work with the complicated normal model	1         relative frequency         Specifically, it allows us to convert standard deviations into percents that are much easier to comprehend.         we convert our data to z-scores and use just one Standard Normal Model N(0,1) and its associated table.

of tables for every possible $N(\mu, \sigma)$ Normal percentile       Read from a table of normal probabilities, it gives the percentage of values in a standard normal distribution found lying below a particular z-score.          The easiest conversion (from standard deviation of the mean, about of the data fall of the mean, about within 2 $68,95,99.7$ gand about within 3. $99.7\%$ $95\%$ Use this TI function $normalcdf(lower z-score, upper z-score)$ $normalcdf(lower z-score, upper z-score)$ if asked to find % or area $output is z-score that may have to be converted back           normal condition, that the shape of the data's distribution is output is z-score that may have to be converted back         $	equation or lug around a myriad	
Normal percentile       Read from a table of normal probabilities, it gives the percentage of values in a standard normal distribution found lying below a particular z-score.         The easiest conversion (from standard deviations to percents) is to remember the of the data fall within 1 standard deviation of the mean, about within 2       68,95,99.7         and about within 3.       99.7%       68%         Use this TI function if fa sked to find % or area       normalcff(lower z-score, upper z-score)       invNorm(area to left)         If given % or area       invNorm(area to left)       output is z-score that may have to be converted back	of tables for every possible $M(x, -)$	
Normal percentile       Read from a table of normal probabilities, it gives the percentage of values in a standard normal distribution found lying below a particular z-score.         The easiest conversion (from standard deviations to percents) is to remember the	$N(\mu,\sigma)$	
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The easiest conversion (from standard deviations to percents) is to remember the		values in a standard normal distribution found lying below a
The eastest conversion (from standard deviations to percents)         is to remember the	The accient conversion (from	particular z-scole.
status do number the	standard deviations to percents)	
Interview of the data fall       68%         within 1 standard deviation of       68%         within 1 standard deviation of       95%         and about	is to remember the	68 95 99 7
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is plotted on the x-axis. Explanatory ( <i>independent/input</i> ) variable		same cases (individuals).
	is plotted on the x-axis.	Explanatory ( <i>independent</i> /input) variable
is plotted on the y-axis. Response ( <i>dependent</i> /output) variable	is plotted on the y-axis.	Response ( <i>dependent</i> /output) variable
Once we make a scatterplot, we <b>1. Form:</b> straight, curved, no pattern, other?	Once we make a scatterplot, we	<b>1. Form:</b> straight, curved, no pattern, other?
about: <b>3. Strength:</b> how much seatter (how closely points follow the form)	about:	2. Direction: + or - slope? 3. Strength: how much scatter (how closely points follow the form)
<b>4 Unusual Features:</b> outliers clusters subgroups?		<b>4 Unusual Features</b> : outliers clusters subgroups?
is a deliberately vague Association	is a deliberately vague	Association
term describing the relationship	term describing the relationship	
between two variables. If	between two variables. If	
positive then increases in one variable generally correspond to increases in the	positive then	increases in one variable generally correspond to increases in the
other.		other.

Correlation describes the	strength
and of the	direction, linear
relationship between two	
variables, without	quantitative
significant	outliers.
3 conditions needed for	1. Quantitative Variables
Correlation:	2. Straight Enough
	3. Outlier
The correlation coefficient is	finding the average product of the z-scores (standardized values).
found by	$\sum z z$
	$r = \frac{\sum x_x x_y}{m-1}$
It's value ranges from	n-1
, it has no, and is	-1 10 + 1
immune to changes of	units.
	scale or order.
Perfect correlation $r = $ ,	$\pm 1$
occurs only when	the points lie exactly on a straight line.
	(you can perfectly predict one variable knowing the other)
No correlation $r = $ ,	0
means that knowing one	
variable gives you	no information about the other variable.
You should give the and	Mean
of x and y along with	Standard deviation
the correlation because	Correlation is not a complete description of two-variable data and
~	the its formula uses means and standard deviations in the z-scores.
Scatterplots and correlation	
coefficients never prove	causation.
Lurking variable	A variable other than x and y that simultaneously affects both
	variables, accounting for the correlation between the two.
To add a categorical variable to	
an existing scatterplot	use a different plot color or symbol for each category.
Chapter 8	Linear Regression
Regression to the mean	Because the correlation is always less than 1.0 in magnitude, each
	predicted $\hat{y}$ tends to be fewer standard deviations from its mean than
	its corresponding x was from its mean. $(\hat{z}_y = rz_x)$
Residual	Observed value – predicted value
	$y - \hat{y}$
If positive	Then the model makes an underestimate.
If negative	Then the model makes an overestimate.
Regression line	The unique line that minimizes the variance of the residuals (sum of
Line of best fit	the squared residuals).
For standardized values	$\hat{z}_y = r z_x$
For actual <i>x</i> and <i>y</i> values	$\hat{y} = b_0 + b_1 x$
To calculate the regression line	rs
in real units (actual x and y	1. Find slope, $b_1 = \frac{1}{s}$
values)	$S_x$
	2. Find y-intercept, plug $b_1$ and point (x, y) [usually (x, y)]
	into $y = b_0 + b_1 x$ and solve for $b_0$
	3. Plug in slope, $b_1$ , and y-intercept, $b_0$ , into $\hat{y} = b_0 + b_1 x$

3 conditions needed for Linear	1. Quantitative Variables
Regression Models:	2. Straight Enough – check original scatterplot & residual scatterplot
/* same as correlation */	3. Outlier (clusters) –points with large residuals and/or high leverage
$R^2$	The square of the correlation, <i>r</i> , between <i>x</i> and <i>y</i>
	The success of the regression model in terms of the fraction of the
	variation of <i>y</i> accounted for by the model.
	(XX% of the variability in y is accounted for by variation in $x$ )
	(differences in x explain XX% of the variability in y)
A high $R^2$	Does not demonstrate the appropriateness of the regression.
Looking at a	a scatterplot of the residuals vs. the <i>x</i> -values.
is a good way to check the	
Straight Enough Condition.	(appropriateness)
It should be	boring: uniform scatter with no direction, shape, or outliers
The is the key to assessing	variation in the residuals
how well the model fits	
(extracts the form).	
Standard deviation of the	Gives a measure of how much the points spread around the
residuals, <i>s</i> <sub>e</sub>	regression line.
$1 - R^2$	The fraction of the original variation left in the residuals.
	(The percentage of variability not explained by the regression line.)
Extrapolations	Dubious predictions of <i>y</i> -values based on <i>x</i> -values outside the range
	of the original data.
Chapter 9	Regression Wisdom
What can go wrong with	1. Inferring Causation
•	2 Extran election
regression:	2.Extrapolation
regression:	3.Outliers and Influential Points
regression:	<ul><li>2.Extrapolation</li><li>3.Outliers and Influential Points</li><li>4.Change in Scatterplot Pattern</li></ul>
regression:	<ul> <li>2.Extrapolation</li> <li>3.Outliers and Influential Points</li> <li>4.Change in Scatterplot Pattern</li> <li>5.Means (or other summaries) rather than actual data.</li> </ul>
regression: High leverage points	<ul> <li>2.Extrapolation</li> <li>3.Outliers and Influential Points</li> <li>4.Change in Scatterplot Pattern</li> <li>5.Means (or other summaries) rather than actual data.</li> <li>Have <i>x</i>-values far from x̄ ((x̄, ȳ) is the fulcrum) and pull more</li> </ul>
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High leverage points With enough leverage the can appear deceptively small.	2.Extrapolation 3.Outliers and Influential Points 4.Change in Scatterplot Pattern 5.Means (or other summaries) rather than actual data. Have <i>x</i> -values far from $\bar{x}$ (( $\bar{x}, \bar{y}$ ) is the fulcrum) and pull more strongly on the regression line. residuals
High leverage points With enough leverage the can appear deceptively small. Leverage and residual produce	<ul> <li>2.Extrapolation</li> <li>3.Outliers and Influential Points</li> <li>4.Change in Scatterplot Pattern</li> <li>5.Means (or other summaries) rather than actual data.</li> <li>Have <i>x</i>-values far from x̄ ((x̄ ,ȳ ) is the fulcrum) and pull more strongly on the regression line.</li> <li>residuals</li> <li>1) Extreme Conformers: don't influence model but do inflate R2</li> </ul>
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Regressions based on	
summaries of the data	Tend to look stronger than the regression on the original data.
Because	Summary statistics are less variable than the underlying data.
Chapter 10	Re-expressing Data: Get It Straight!
Re-expression	A means of altering the data to achieve the conditions/structure
	necessary to utilize particular summaries or models.
Several reasons to consider a	1. Make the form of a scatterplot straighter.
re-expression:	2. Make the scatter in a scatterplot more consistent (not fan shaped).
	3. Make the distribution of a variable (histogram) more symmetric.
	4. Make the spread across different groups (boxplots) more similar.
Ladder of Powers	Orders the effects that the re-expressions have on the data
	$2 1 \frac{1}{2} 0 -\frac{1}{2} -1$
	$y^2$ y $\sqrt{y}$ log y $-1/\sqrt{y}$ $-1/y$
A good starting point is	taking logs.
If all else fails	try whacking the data with two logs (log x and log y).
Base 10 logs are roughly	One less than the number of digits needed to write the number.
Re-expression limitations:	1. Can't straighten scatterplots that turn around.
	2. Can't re-express "-" data values with $\sqrt{(+\text{constant to shift} > 0)}$
	3. Minimal affect on data values far from 1-100. (-constant to shift)
	4. Can't unify multiple modes.
When discussing the accuracy	Appropriateness of the model as indicated by the residual plot
or confidence of the linear	
regression model be sure to	Success of the model as indicated by R <sup>2</sup>
comment on both the &	
Part III	Gathering Data
Part III Chapter 11	Gathering Data Understanding Randomness
Part III Chapter 11 What is it about random	Gathering Data         Understanding Randomness         1. Nobody can guess the outcome in advance.         2. Outcome in advance.
Part III         Chapter 11         What is it about random         selection that makes it seem         fair2	Gathering DataUnderstanding Randomness1. Nobody can guess the outcome in advance.2. Outcomes are equally likely.
Part III Chapter 11 What is it about random selection that makes it seem fair?	Gathering Data         Understanding Randomness         1. Nobody can guess the outcome in advance.         2. Outcomes are equally likely.
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Trial	The sequence of several components representing events that we are
D	pretending will take place.
Response variable	The result of each trial with respect to what we were interested in.
Chapter 12	Sample Surveys
Population	The entire group of individuals or instances about whom we hope to
	learn, but examining all of them is usually impractical, if not
	impossible.
Sample	A (representative) subset of a population, examined in hope of
	learning about the population.
Sample survey	A study that asks questions of a sample drawn from some population
	in the hope of learning something about the entire population.(Polls)
Statistic	Any summary calculated from the (sampled) data.
They are written in	Latin $(x, s, r, b, p)$
Parameters	Key numbers in mathematical models used to represent reality.
They are written in	Greek $(\mu, \sigma, \rho, \beta, p)$
Population parameter	A numerically valued attribute of a model for a population, often
Sample statistic	Correspond to and thus estimate a population parameter
Banragantativa Sampla	Correspond to, and thus estimate, a population parameter.
Representative Sample	statistics computed from it accurately reflect the corresponding
Bias	Any systematic failure of a sampling method to represent its
Dias	nonulation. It is almost impossible to recover from
5 common bias errors:	1 Nonresponse – when a large fraction of those sampled will not or
(Biases I hope to)	cannot respond
	2. Voluntary response – individuals can choose on their own
	whether to participate in the sample. Always yields invalid
	samples.
	3. <b>R</b> esponse – when respondents' answers might be affected by
	survey design, such as question wording or interviewer behavior
	4. Convenience – when the sample is comprised of individuals
	readily available. Always yields a non-representative sample.
	3. Undercoverage – when individuals from a subgroup of the
	population are selected less often than they should be.
is often the best use of	Reducing biases
time and resources when	
sampling or surveying.	
Randomization	The best defense against bias.
	(stirring to make sure that on average the sample looks like the rest
	of the population)
Simple random sample (SKS)	A sample in which each set of n elements in the population has an
	equal chance of selection. The standard method of utilizing redomization to make the semple
	representative of the population of interest
Sampling variability	The natural tendency of randomly drawn samples to differ from
Sampling variability	each other
The precision of the statistics of	
The precision of the statistics of	

a sample depend on	the sample size (soup spoon)
not	its fraction of the larger population.
Census	A sample that consists of the entire population.
Sampling frame	A list of individuals, which clearly defines but may not be
	representative of the entire population, from which the sample is
	drawn.
Stratified samples	These samples can reduce sampling variability by identifying
	homogeneous subgroups and then randomly sampling within each.
Cluster samples	These samples randomly select among heterogeneous subgroups that
	each resemble the population at large, making our sampling tasks
	more manageable.
Systematic samples	These samples can work, when there is no relationship between the
	order of the sampling frame and the variables of interest, and are
	often the least expensive method of sampling. But we still want to
	start them randomly.
Multistage sample	A sampling scheme that combines several sampling methods.
Identify the W's:	
Why	Population and associated sampling frame.
What	Parameter of interest and variables measured.
Who	Sample actually drawn.
When, Where, and How	Given by the sampling plan.
/* previously Who < What */	
Chapter 13	Experiments and Observational Studies
Observational study	A study based on data in which no manipulation of factors has been
	employed (researchers don't assign choices). Usually focuses on
	estimating differences between groups but is not possible to
	demonstrate a causal relationship. Often used when an experiment
Detressestive	is impractical.
Retrospective	Subjects are selected and then their previous conditions or behaviors
Prograativa	are determined.
Flospective	subjects are followed to observe future outcomes. No treatments
To prove a cause and effect	are deliberately applied.
relationship we need to perform	a vand experiment.
relationship we need to perform	
<u>An experiment</u>	manipulates factor levels
to create treatments	randomly assigns subjects
to these treatment levels and	
then	compares the responses of the subject groups
across treatment levels	(boxplots are often a good choice for displaying results of groups)
Factor	A variable whose levels are controlled by the experimenter
Level	The specific values that the experimenter chooses for a factor.
Treatment	The process intervention or other controlled circumstance applied
	to randomly assigned experimental units. Treatments are the
	different levels of a single factor or are made up of combinations of
	levels of two or more factors.
are individuals on whom	Experimental units
Who When, Where, and How /* previously Who < What */ Chapter 13 Observational study Retrospective Prospective To prove a cause-and-effect relationship we need to perform  An experiment to create treatments, to these treatment levels, and then across treatment levels. Factor Level Treatment	Sample actually drawn. Given by the sampling plan. <b>Experiments and Observational Studies</b> A study based on data in which no manipulation of factors has been employed (researchers don't assign choices). Usually focuses on estimating differences between groups but is not possible to demonstrate a causal relationship. Often used when an experiment is impractical. Subjects are selected and then their previous conditions or behaviors are determined. Subjects are followed to observe future outcomes. No treatments are deliberately applied. a valid experiment. manipulates factor levels randomly assigns subjects compares the responses of the subject groups (boxplots are often a good choice for displaying results of groups) A variable whose levels are controlled by the experimenter. The specific values that the experimenter chooses for a factor. The process, intervention, or other controlled circumstance applied to randomly assigned experimental units. Treatments are the different levels of a single factor or are made up of combinations of levels of two or more factors.

Usually called or	Subjects
when human.	Participants
Response	A variable whose values are compared across different treatments.
The 4 principals of	1. <b>Control</b> sources of variation other than the factors we are testing
experimental design:	by making conditions as similar as possible for all treatment
	groups.
	2. <b>Randomize</b> subjects to treatments to even out effects that we
	2 <b>Deplicate</b> over as many subjects as possible. Would like to get
	results from a representative sample of the population of interest
	4 <b>Block</b> and then randomize within to reduce the effects of
	identifiable attributes of the subjects that cannot be controlled.
Control group	The experimental units assigned to a baseline treatment level.
	typically either the default treatment, which is well understood, or a
	null, placebo treatment.
	Their responses provide a basis for comparison.
Statistically significant	When an observed difference is too large for us to believe that it is
	likely to have occurred naturally (only by chance).
Placebo	A (fake) treatment known to have no effect, administered so that all
	groups experience the same conditions.
Placebo effect	The tendency of many human subjects (often 20% or more of
	experimental subjects) to show a response even when administered a
יו יות	placebo.
Blinding	individuals associated with an experiment are not aware of now
2 main classes of individuals	1 those who could influence the results (subjects, treatment
who can affect the outcome of	administrators, or technicians)
an experiment:	2 those who evaluate the results (judges treating physicians etc.)
Single-blind	When every individual in <i>either</i> of these classes is blinded.
Double-blind	When everyone in <i>both</i> classes is blinded.
Block	Same idea for experiments as stratifying is for sampling.
	Group together subjects that are similar and randomize within those
	groups as a way to remove unwanted variation (of the differences
	between the groups so that we can see the differences caused by the
	treatments more clearly)
	(Doing parallel experiments on different groups.)
Matching	In a retrospective or prospective study, subjects who are similar in
	ways not under study may be paired and then compared with each
	variation in much the same way as blocking
Designs:	variation in much the same way as blocking.
Randomized block design	The randomization occurs only within blocks
Completely random design	All experimental units have an equal chance of receiving any
	particular treatment.
The best experiments are	Randomized, comparative, double-blind, placebo-controlled.
usually:	r , , , r
Lurking (Confounding)	
variables are outside influences	

that make it we	harder to understand the relationship
are modeling with	regression and observational studies (a designed experiment).
Lurking variable	Creates an association between two other variables that tempts us to
	think that one may cause the other.
	[regression analysis or observational study]
~ ~ ~	
Confounding	Some other variable associated with a factor has an effect on the
	response variable. [experiments]
	Arises when the response we see in an experiment is at least
	partially attributable to uncontrolled variables.
Part IV	Kandomness and Probability
Chapter 14	From Kandomness to Probability
Probability	The proportion of times the event occurs in many repeated trials of a
The miles and concents of	Pandom phenomenon. (the long-term relative frequency of an event)
republic give us a language	kandom phenomena.
to talk and think about	
Trial	A single attempt or realization of a random phenomenon
Outcome	The value measured observed or reported for each trial
Event	A combination of outcomes usually for the purpose of attaching a
Lvent	probability to them. Denoted with <b>bold</b> capital letters <b>A B</b> or <b>C</b>
Independent	The outcome of one trial doesn't influence or change the outcome of
macpendent	another
The Law of Large Numbers	The long-run relative frequency of repeated independent events
(LLN)	settles down to the true probability as the number of trials increases.
Law of Averages	Assumes that the more something hasn't happened, the more likely
(The lesson of LLN)	it becomes.
	Random processes don't need to compensate in the short run to get
	back to the right long-run probabilities. (Streaks happen - the coin
	can't remember what happened and make things come out right.)
is just a casual term	Relative frequencies
for probability.	[at the beginning of the year it was a code-word for percent]
Probability of the event <b>A</b>	The likelihood of the event's occurrence
	$P(\mathbf{A}) = \frac{\text{number of outcomes in } \mathbf{A}}{\text{if outcomes are equally likely}}$
	total number of outcomes
	$0 \le P(\mathbf{A}) \le 1$
Sample Space, <i>S</i>	The collection of all possible outcome values.
Something Has to Happen Rule	The sum of the probabilities of all possible outcomes must be 1.
	$P(\mathbf{S}) = 1$
Complement Rule	The probability of an event occurring is 1 minus the probability that
D	1t doesn't occur. $P(\mathbf{A}) = 1 - P(\mathbf{A}^c)$
Disjoint	I wo events that share no outcomes in common, mutually exclusive.
The	(outcomes cannot nappen at the same time, one prevents the other)
If <b>A</b> and <b>B</b> are disjoint events	
Then the probability of $\mathbf{A}$ or $\mathbf{P}$	$P(\mathbf{A}    \mathbf{B}) - P(\mathbf{A}) \perp P(\mathbf{B})$ $\cdot    - Union$
An assignment of probabilities	Fach probability is between 0 and 1(inclusive)
to outcomes is legitimate if	The sum of the probabilities is 1
to outcomes is regulated in	The sum of the productities is i

The says:	Multiplication Rule
If <b>A</b> and <b>B</b> are independent	
events,	
Then the probability of <b>A</b> and <b>B</b>	$P(\mathbf{A} \cap \mathbf{B}) = P(\mathbf{A}) \times P(\mathbf{B})$ ; $\cap$ = Intersection
Chapter 15	Probability Rules!
and should	Venn diagrams, two-way contingency tables
be used to display the sample	
space and aid probability	
calculations.	
When working with	
probabilities:	
"or" is the of the two	Union
events and translates into	+
"and" is the of the two	Intersection
events and translates into	X
"not" & "at least" often	
indicate	Complement
The says:	General Addition Rule (avoids double counting when not disjoint)
For any two events, <b>A</b> and <b>B</b> ,	
The probability of <b>A</b> or <b>B</b>	$P(\mathbf{A} \cup \mathbf{B}) = P(\mathbf{A}) + P(\mathbf{B}) - P(\mathbf{A} \cap \mathbf{B})$
Conditional Probability	$P(\mathbf{A} \cap \mathbf{B})$
[restricts the "Who"]	$P(\mathbf{B}   \mathbf{A}) = \frac{\langle \mathbf{A} \rangle}{P(\mathbf{A})}$
	$P(\mathbf{B}   \mathbf{A})$ is read "the probability of <b>B</b> given <b>A</b> ."
The says:	General Multiplication Rule (adjusts for non-independence)
For any two events, <b>A</b> and <b>B</b> ,	
The probability of <b>A</b> and <b>B</b>	$P(\mathbf{A} \cap \mathbf{B}) = P(\mathbf{A}) \times P(\mathbf{B} \mathbf{A})$
Events <b>A</b> and <b>B</b> are disjoint	When $P(\mathbf{B} \mathbf{A}) = 0$ (From conditional probability formula because
	the intersection as shown in a Venn diagram is 0.) /*see IL notes*/
Events <b>A</b> and <b>B</b> are independent	When $P(\mathbf{B} \mathbf{A}) = P(\mathbf{B})$
Tree diagram	Useful for showing sequences of (conditional) events and
	when utilizing the General Multiplication Rule.
	The probabilities of each set of branches as well as disjoint final
	outcomes sum to 1.
Reverse Conditioning	
We have $P(\mathbf{A} \mathbf{B})$ but want	$P(\mathbf{B} \mathbf{A})$
We need to find and	$P(\mathbf{A} \cap \mathbf{B}), P(\mathbf{A})$
With the help of	a tree diagram