Statistical Significance and Bivariate Tests

BUS 735: Business Decision Making and Research

Goals

- Specific goals:
  - Re-familiarize ourselves with basic statistics ideas: sampling distributions, hypothesis tests, p-values.
  - Be able to distinguish different types of data and prescribe appropriate statistical methods.
  - Conduct a number of hypothesis tests using methods appropriate for questions involving only one or two variables.
- Learning objectives:
  - LO1: Be able to construct and test hypotheses using a variety of bivariate statistical methods to compare characteristics between two populations.
  - LO6: Be able to use standard computer packages such as SPSS and Excel to conduct the quantitative analyses described in the learning objectives above.

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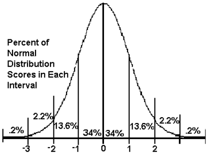
Probability Distribution

- **Probability distribution:** summary of all possible values a variable can take along with the probabilities in which they occur.
- Usually displayed as:

Picture



Table

z	0.00	0.01	0.02	0.03	0.04	0.05
0.0	0.5000	0.5040	0.5080	0.5120	0.5159	0.5199
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749

Formula

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

- **Normal distribution:** often used "bell shaped curve", reveals probabilities based on how many standard deviations away an event is from the mean.

Sampling distribution

- Imagine taking a sample of size 100 from a population and computing some kind of statistic.
- The statistic you compute can be anything, such as: mean, median, proportion, difference between two sample means, standard deviation, variance, or anything else you might imagine.
- Suppose you repeated this experiment over and over: take a sample of 100 and compute and record the statistic.
- A **sampling distribution** is the probability distribution *of the statistic*
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  NO! They may coincidentally have the same shape though.

Example

- Sampling Distribution Simulator
- In reality, you only do an experiment once, so the sampling distribution is a hypothetical distribution.
- Why are we interested in this?

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- The average of the sample statistics is equal to the true population parameter.
- Want the variance *of the sampling distribution* to be as small as possible. Why?
- Want the *sampling distribution* to be normal, regardless of the distribution of the population.

Central Limit Theorem

- Given:
  - Suppose a RV x has a distribution (it need not be normal) with mean μ and standard deviation σ.
  - Suppose a *sample mean* ($\bar{x}$) is computed from a sample of size n.
- Then, if n is sufficiently large, the sampling distribution of $\bar{x}$ will have the following properties:
  - The sampling distribution of $\bar{x}$ will be normal.
  - The mean of the sampling distribution will equal the mean of the population (consistent):

$$\mu_{\bar{x}} = \mu$$

  - The standard deviation of the sampling distribution will decrease with larger sample sizes, and is given by:

$$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$$

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The probability the sample mean is greater than $7.5lbs$ is:

$$P(\bar{x} > 7.5) = P(z > 1.826) = 0.0339$$

Example 2

Suppose average birth weight is $\mu = 7lbs$, and the standard deviation is $\sigma = 1.5lbs$.

What is the probability that a randomly selected baby will have a weight of 7.5lbs or more? What do you need to assume to answer this question?

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The probability that a baby is greater than 7.5lbs is:

$$P(x > 7.5) = P(z > 0.33) = 0.3707$$

Example 3

- Suppose average birth weight of all babies is $\mu = 7 lbs$, and the standard deviation is $\sigma = 1.5 lbs$.
- Suppose you collect a sample of 30 newborn babies whose mothers used illegal drugs during pregnancy.
- Suppose you obtained a sample mean $\bar{x} = 6 lbs$. If you assume the mean birth weight of babies whose mothers used illegal drugs has the same sampling distribution as the rest of the population, what is the probability of getting a sample mean this low or lower?

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The probability the sample mean is less than or equal to $6 lbs$ is:

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The probability the sample mean is less than or equal to 6*lbs* is:

$$P(\bar{x} < 6) = P(z < -3.65) = 0.000131$$

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That is, if using drugs during pregnancy actually does still lead to an average birth weight of 7 pounds, there was only a 0.000131 (or 0.0131%) chance of getting a sample mean as low as six or lower. This is an extremely unlikely event if the assumption is true. Therefore it is likely the assumption is not true.

Statistical Hypotheses

- A **hypothesis** is a claim or statement about a property of a population.
  - Example: The population mean for systolic blood pressure is 120.
- A **hypothesis test** (or **test of significance**) is a standard procedure for testing a claim about a property of a population.
- Recall the example about birth weights with mothers who use drugs.
  - Hypothesis: Using drugs during pregnancy leads to an average birth weight of 7 pounds (the same as with mothers who do not use drugs).

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Null and Alternative Hypotheses

- The **null hypothesis** is a statement that the value of a population parameter (such as the population mean) *is equal to* some claimed value.
  - H_0: $\mu = 7$.
- The **alternative hypothesis** is an alternative to the null hypothesis; a statement that says a parameter differs from the value given in the null hypothesis.
  - H_a: $\mu < 7$.
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- In hypothesis testing, assume the null hypothesis is true until there is strong statistical evidence to suggest the alternative hypothesis.
- Similar to an "innocent until proven guilty" policy.

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P-values

- The P-value of the test statistic, is the area of the sampling distribution from the sample result in the direction of the alternative hypothesis.
- Interpretation: If the null hypothesis is correct, than the p-value is the probability of obtaining a sample that yielded your statistic, or a statistic that provides even stronger evidence of the null hypothesis.
- The p-value is therefore a measure of *statistical significance*.
  - If p-values are very small, there is strong statistical evidence in favor of the alternative hypothesis.
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Types of Data

- Nominal data: consists of categories that cannot be ordered in a meaningful way.
- Ordinal data: order is meaningful, but not the distances between data values.
  - Excellent, Very good, Good, Poor, Very poor.
- Interval data: order is meaningful, *and* distances are meaningful. However, there is *no natural zero*.
  - Examples: temperature, time.
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Single Mean T-Test

- Test whether the population mean is equal or different to some value.
- Uses the sample mean its statistic.
- Why T-test instead of Z-test?
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- Dataset: average pay for public school teachers and average public school spending per pupil for each state and the District of Columbia in 1985.
- Download dataset `eduspending.xls`.
- Conduct the following exercises:
  - Show some descriptive statistics for teacher pay and expenditure per pupil.
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- Data from Montana residents in 1992 concerning their outlook for the economy.
- All data is ordinal or nominal:
  - AGE = 1 under 35, 2 35-54, 3 55 and over
  - SEX = 0 male, 1 female
  - INC = yearly income: 1 under \$20K, 2 20-35\$K, 3 over \$35K
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  - AREA = 1 Western, 2 Northeastern, 3 Southeastern Montana
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- Why?
  - Ordinal data: cannot compute sample means (they are meaningless), only median is meaningful.
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- Sign test: can use tests for proportions for testing the median.
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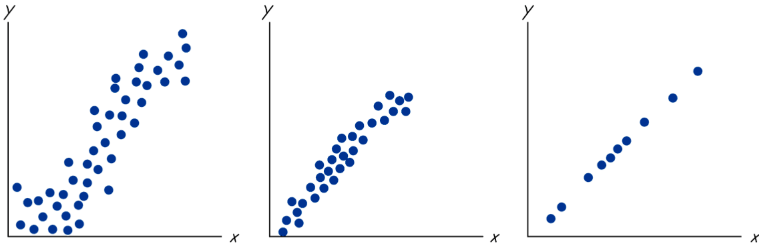
Positive linear correlation



(a) Positive correlation between x and y

(b) Strong positive correlation between x and y

(c) Perfect positive correlation between x and y

- Positive correlation: two variables move in the same direction.
- Stronger the correlation: closer the correlation coefficient is to 1.
- Perfect positive correlation: $\rho = 1$

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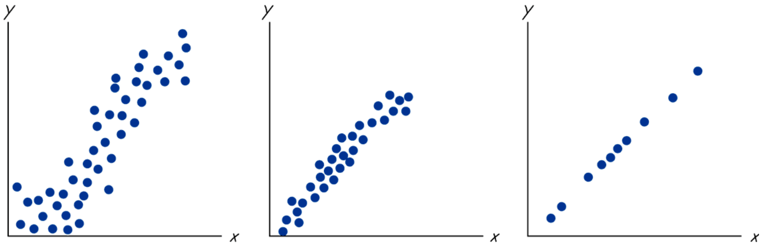

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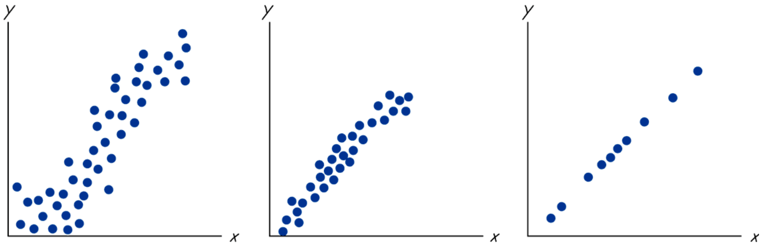

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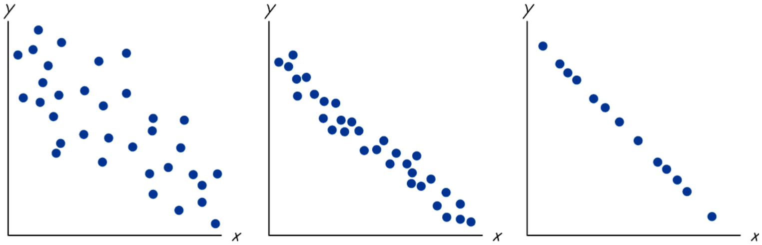

(d) Negative correlation between x and y

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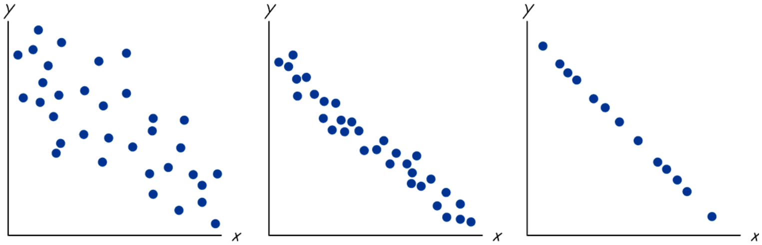

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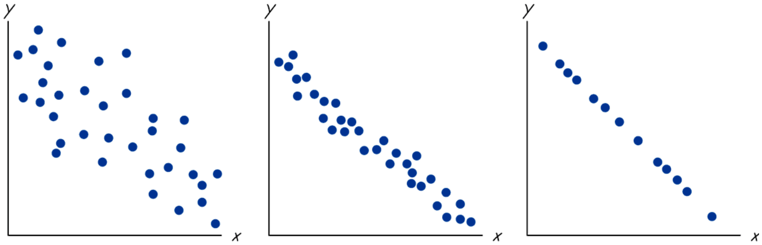

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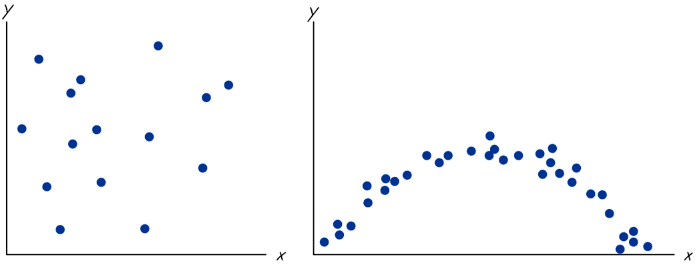

(g) No correlation between x and y

(h) Nonlinear relationship between x and y

- Panel (g): no relationship at all.
- Panel (h): strong relationship, but not a *linear* relationship.
  - Cannot use regular correlation to detect this.

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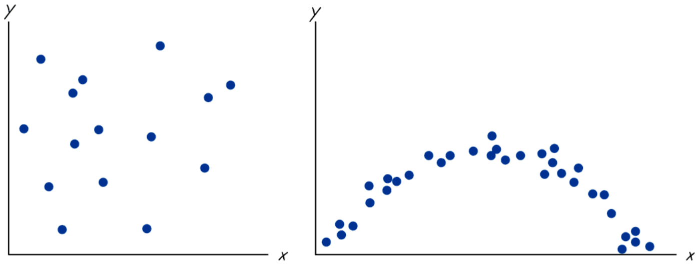

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Example: Public Expenditure

- Data from 1960! about public expenditures per capita, and variables that may influence it:
  - Economic Ability Index
  - Percentage of people living in metropolitan areas.
  - Percentage growth rate of population from 1950-1960.
  - Percentage of population between the ages of 5-19.
  - Percentage of population over the age of 65.
  - Dummy variable: Western state (1) or not (0).
- Is there a statistically significant linear correlation between the percentage of the population who is young and the public expenditure per capita?
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Difference in Means (Independent Samples)

- Suppose you want to know whether the mean from one population is larger than the mean for another.
- Examples:
  - Compare sales volume for stores that advertise versus those that do not.
  - Compare production volume for employees that have completed some type of training versus those who have not.
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- Hypotheses:
  - Null hypothesis: the difference between the two means is zero.
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  - the variance in the two populations is the same (more powerful test), or...
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  - To guide you, SPSS also reports Levene's test for equality of variance (Null - variances are the same).

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- Mann-Whitney U test: nonparametric test to determine difference in *medians*.
- Assumptions:
  - Samples are independent of one another.
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- Really simple: for each individual subtract the before treatment measure from the after treatment measure (or vice-versa).
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