

# Design and Analysis of Experiments

## 05 - Statistical Inference

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*“Nothing in life is to be feared,  
it is only to be understood.  
Now is the time to understand more,  
so that we may fear less.”*

Marie Skłodowska Curie  
1867–1934  
Polish-French physicist and chemist.



# Statistical Inference

## Introduction

Definitions such as point estimators and statistical intervals belong to a branch of statistical theory known as *descriptive statistics*, that is, methods that are focused on accurately describing characteristics such as location or uncertainty about a given population parameter;

While these concepts are certainly important, in many cases description is not enough – one may need decision-making tools to deal with information from random samples, tools that allow a researcher to perform *inference* with a quantifiable degree of certainty.

# Statistical hypotheses

## Scientific Hypotheses

A *hypothesis* is a proposed explanation for an observable phenomenon.

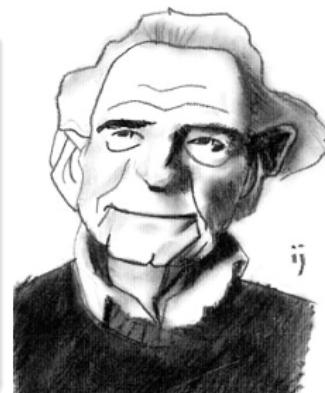
Scientific hypotheses must satisfy (at least) two conditions:

- Falsifiability;
- Testability;

*“The more we learn about the world, and the deeper our learning, the more conscious, specific, and articulate will be our knowledge of what we do not know, our knowledge of our ignorance.”*

Sir Karl R. Popper  
(1902-1994)

Austro-British philosopher



# Statistical Hypothesis

The hypothetico-deductive model

The *hypothetico-deductive model* of construction of scientific knowledge includes:

- Formulation of falsifiable hypotheses;
- Refutation or corroboration of the hypotheses by the data;
- Predictive power;
- Comparison between alternative hypotheses - principle of parsimony (Ockham's razor);



*“Numquam ponenda est pluralitas sine necessitate.”*

William of Ockham  
(1287-1347)

English philosopher and theologian

# Statistical hypotheses

## Comparing Competing Hypotheses

As multiple, competing hypotheses can be proposed to explain any given phenomenon, it is common to contrast these proposed explanations using a number of criteria.

Besides the required testability / falsifiability and the desired parsimony, common ones include:

- Scope: how applicable is the hypothesis to multiple instances of the phenomenon it addresses?
- External consistency: how well does the hypothesis fit with existing, well-accepted knowledge systems?

# Statistical Hypotheses

## Definitions

*Statistical hypotheses* are defined as objective statements about parameters of one or more populations;

**Attention:** the statements in statistical hypotheses are about parameters of the *population or model, not the sample*.

The *null hypothesis significance testing* (NHST) approach involves the contrast between *null* and *alternative* hypotheses.

### Null hypothesis ( $H_0$ )

- Absence of effects;
- *Conservative* model.

**Example:**  $H_0 : \mu = 25$

### Alternative hypothesis ( $H_1$ )

- Presence of some effect;
- Existence of something “new”.

**Example:**  $H_1 : \mu \neq 25$

# Statistical Hypotheses

## Definitions

Determination of the reference value for the null hypothesis  $H_0$ :

- Previous knowledge about the process (investigation of changes);
- Value obtained from theory or models (model validation);
- Project requirements (investigation of system compliance);

Hypothesis testing involves:

- Obtaining a sample;
- Calculating test statistics;
- Deciding based on the computed value;

# Statistical Hypotheses

## Example



Suppose you own a company that sells green peas to large customers, and that you want to determine whether your 50kg sacks really contain their nominal weight (at least on average).

In this case the null hypothesis could be defined as: *the average net weight of a sack is 50kg*, and the alternative of interest could be expressed as the complementary inequality.

$$\begin{cases} H_0 : \mu = 50\text{kg} \\ H_1 : \mu \neq 50\text{kg} \end{cases}$$

Suppose still that  $n = 10$  sacks are randomly sampled, and their contents are weighted using a reliable scale;

# Statistical Hypotheses

## Example



Notice that we are already adopting a number of underlying assumptions (both statistical and technical):

- The mean is a good measure for our question of interest (under-underlying assumptions: the variance is small enough, the customers purchase larger quantities so that on average the deal is fair, ...)
- The sacks sampled are representative of our population of interest (i.e., of the sacks that are actually going to be sold);
- The contents of the sacks are only green peas (no significant amounts of stones or other contaminants);
- ...

# Statistical Hypotheses

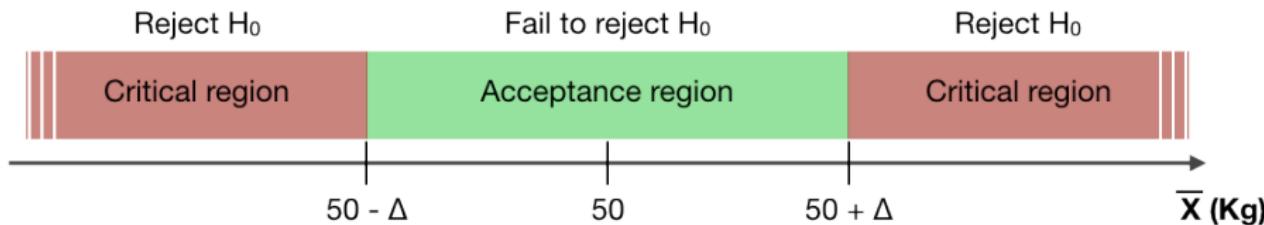
Example



Since the sample mean  $\bar{X}$  is a good estimator of the real mean  $\mu$ , common sense suggests that:

- If  $\bar{x} \cong 50\text{kg}$  - corroboration of  $H_0$ ;
- If  $\bar{x} \ll 50\text{kg}$  or  $\bar{x} \gg 50\text{kg}$  - refutation of  $H_0$ ;

That is, we can use  $\bar{x}$  as the basis for a test. But how to define a *critical region* for the rejection of  $H_0$ ?



# Inferential Errors

## Type I error

**Type I error** (false positive): rejecting the null hypothesis when it is true.

The probability of occurrence of a false positive in any hypothesis testing procedure is generally known as the *significance level* of the test, represented by Greek letter  $\alpha$ :

$$\alpha = P(\text{type I error}) = P(\text{reject } H_0 | H_0 \text{ is true})$$

Another frequently used term is the *confidence level* of the test, given by  $(1 - \alpha)$  or, sometimes, as  $100(1 - \alpha)\%$ .

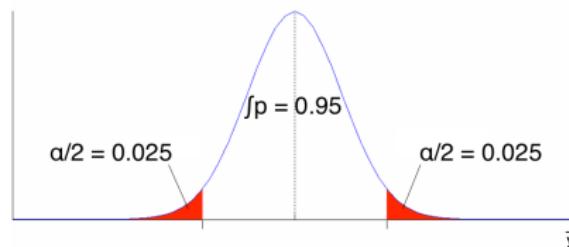
# Inferential Errors

## Type I error

For a given sample, the selected value of  $\alpha$  defines the critical threshold for the rejection of  $H_0$ .

If  $H_0$  is true (i.e., if  $\mu = 50\text{kg}$ ), the distribution of  $\bar{X}$  is approximately Normal (assuming that the population is Normal, OR that the CLT conditions are met and  $N$  is suitably large), with average  $50\text{kg}$  and standard error  $(\sigma/\sqrt{n}) \text{ kg}$ ;

For a desired Type-I error probability  $\alpha = 0.05$ , the critical values of the distribution of  $\bar{X}$  are the ones for which the probability content within the acceptance region under the null hypothesis is  $1 - \alpha = 0.95$ .



# Inferential Errors

## Type II error

**Type II error** (false negative): failure to reject the null hypothesis when it is false.

The probability of occurrence of a false negative in any hypothesis testing procedure is generally represented by the Greek letter  $\beta$ :

$$\beta = P(\text{type II error}) = P(\text{not reject } H_0 | H_0 \text{ is false})$$

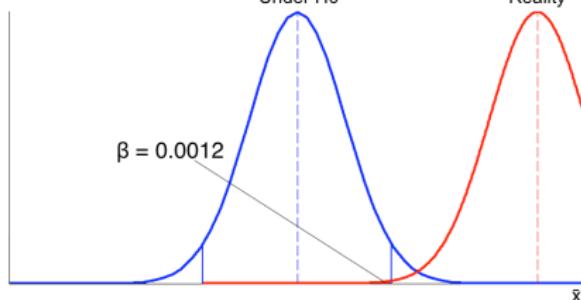
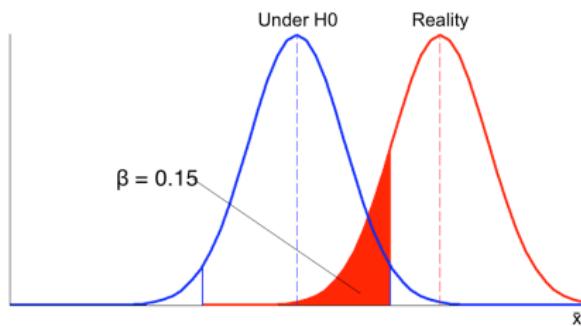
The quantity  $(1 - \beta)$  is known as *power* of the test, and quantifies its sensitivity to effects that violate the null hypothesis.

# Inferential Errors

## Type II error

Unlike the Type-I error, the definition of the Type-II error rate requires further specification of the value of the parameter being investigated under the alternative hypothesis;

The probability of failing to reject a false  $H_0$  is strongly dependent on the magnitude of the difference between the value under  $H_0$  and the real value of the parameter.



# Inferential Errors

## Type II error

The power of a test is governed by several factors:

- Controllable: significance level, sample size, directionality of  $H_1$ ;
- Uncontrollable: real value of the parameter, variance;

If  $H_0$  is false, the smaller the magnitude of the difference between the real value of the parameter and the one under the null hypothesis, the greater the probability of a type II error - ***but the practical importance of the effect gets smaller.***

# Inferential Errors

## Considerations

**Type I error** ( $\alpha$ ) depends only on the distribution of the null hypothesis  
- easier to control;

**Type II error** ( $\beta$ ) depends on the real value of the parameter - more difficult to specify and control;

These characteristics lead to the following classification of the conclusions obtained from the test of hypotheses:

- Rejection of  $H_0$  - *strong* conclusion;
- Failure to reject  $H_0$  - *weak* conclusion (but we can strengthen it);

It is important to remember that failing to reject  $H_0$  does not mean that there is evidence in favor of  $H_0$  - it only suggests that it is a better model than the alternative.

# Hypothesis Testing

## General procedure

- Identify the parameter of interest;
- Define  $H_0$  and  $H_1$  (one- or two-sided);
- Determine desired  $\alpha, \beta$ ;
- Define minimally interesting effect  $\delta^*$ ;
- Determine the test statistic and critical region;
- Calculate sample size;
- Compute the statistic;
- Decide whether or not to reject  $H_0$ ;



# Hypothesis Testing

Mean of a Normal distribution, variance known



Back to the green peas example, we want to determine if there is any significant deviation on the mean weight of the sacks. Assume (for now) that the variance of the process is known. The test hypotheses are defined as:

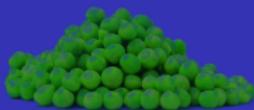
$$\begin{cases} H_0 : \mu = 50\text{kg} \\ H_1 : \mu \neq 50\text{kg} \end{cases}$$

Let the desired significance level be  $\alpha = 0.05$ ;

Given these characteristics, we expect that the sampling distribution of  $\bar{X}$  is Normal, with  $\text{Var}(\bar{X}) = \sigma^2/n$  and, if  $H_0$  is true, a mean of  $\mu_{\bar{X}} = \mu_0 = 50$ ;

# Hypothesis Testing

Mean of a Normal distribution, variance known



Based on these characteristics, the standardized variable

$$Z_0 = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$$

will be distributed, under the null hypothesis, according to the standard Normal,  $\mathcal{N}(0, 1)$ .

This result implies that:

$$P(z_{\alpha/2} \leq Z_0 \leq z_{1-\alpha/2} \mid H_0 \text{ is true}) = 1 - \alpha$$

which provides a selection criterion between  $H_0$  and  $H_1$ :

- If  $z_{\alpha/2} > Z_0$  or  $z_{1-\alpha/2} < Z_0$ , reject  $H_0$  with confidence  $(1 - \alpha)$ ;
- Otherwise, there is not enough evidence to reject  $H_0$  at this confidence level;

# Hypothesis Testing

Mean of a Normal distribution, variance known



Assume that we got  $\bar{x} = 49.65\text{kg}$  from our  $n = 10$  observations, and that we know that  $\sigma = 1\text{kg}$ . In this case,

$$z_0 = \frac{49.65 - 50}{1/\sqrt{10}} = -1.113$$

The critical values of the standard Normal distribution at the significance level  $\alpha = 0.05$  are  $[z_{0.025}, z_{0.975}] = [-1.96, 1.96]$ ;

Since  $z_0 \in [-1.96, 1.96]$ , we can conclude that there is not enough evidence to reject  $H_0$  at the 95% confidence level.

# Hypothesis Testing

Mean of a Normal distribution, variance unknown



Suppose now a more realistic situation in which the real variance is unknown. Besides, assume that we are interested in detecting only negative deviations from the nominal contents of the package.

The test hypotheses can be defined as:

$$\begin{cases} H_0 : \mu \geq 50\text{kg} \\ H_1 : \mu < 50\text{kg} \end{cases}$$

Assume also that we want to be more conservative, so we pick a significance level  $\alpha = 0.01$ ;

In this case, **if  $H_0$  is true**, we have that

$$T_0 = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \sim t^{(n-1)}$$

# Hypothesis Testing

Mean of a Normal distribution, variance unknown



From the same data used earlier,  $\bar{x} = 49.65\text{kg}$ ,  $n = 10$ ,  $s = 0.697\text{kg}$ :

$$t_0 = \frac{49.65 - 50}{0.697/\sqrt{10}} = -1.597$$

The critical value of this test statistic for the desired significance is  $t_{\alpha}^{(n-1)} = t_{0.01}^{(9)} = -2.82$ , which means that under  $H_0$  there is a 99% chance that the test statistic will yield a value greater than this number.

Given that  $t_0 > -2.82$ , we conclude that the evidence is insufficient to reject  $H_0$  at the 99% confidence level;

# Hypothesis Testing

Mean of a Normal distribution, variance unknown



```
> my.sample <- read.table("../data files/greenpeas.txt")  
  
> t.test(my.sample,  
+         alternative = "less",  
+         mu = 50,  
+         conf.level = 0.99)
```

```
One Sample t-test  
data: my.sample  
t = -1.5969, df = 9, p-value = 0.07237  
alternative hypothesis: true mean is less than 50  
99 percent confidence interval:  
-Inf 50.2699  
sample estimates:  
mean of x  
49.648
```

	greenpeas.txt
1	50.03
2	49.73
3	49.53
4	50.64
5	49.68
6	47.99
7	49.85
8	50.20
9	49.51
10	49.32

# Hypothesis Testing

## Reporting results

Description of the results:

*(In)Sufficient evidence for rejecting  $H_0$  at the significance level  $\alpha$ .*

Even though it is correct, this description is relatively poor:

- It does not provide information on the intensity of the evidence for rejection/non-rejection;
- It imposes a predetermined significance level to the consumer of the information;
- Does not provide information the magnitude of the effect found or the sensitivity of the test.

# Hypothesis Testing

## The p-value

**p-value:** *the lowest significance level that would lead to the rejection of  $H_0$  for the available data.*

Can be interpreted as the probability under  $H_0$  of the test statistic assuming a value at least as extreme as the one obtained;

For the previous example, the p-value could be calculated as:

$$p = P(t_0 \leq -1.597 | H_0 = \text{TRUE}) = \int_{-\infty}^{-1.597} t^{(9)} dt = 0.07237$$

*A priori* definition of the significance level is still important!

# Hypothesis Testing

p-values, significance and effect sizes

Statistical  $\times$  practical significance: p-values can be made arbitrarily small, if  $n$  is big enough;

As an example, suppose a test of  $H_0 : \mu = 500$  against a two-sided alternative, with  $n = 5000$ ,  $\bar{x} = 499$ ,  $s = 5$ . In this case we would have:

- $t_0 = -14.142$ ;
- $p = 1.02 \times 10^{-23}$ ;

Is it really *that* significant?

# Hypothesis Testing

p-values, significance and effect sizes

To “tell the whole story” of the experiment, it is necessary to use **effect size estimators** alongside the tests of statistical significance;

While there are whole books on the subject<sup>c</sup>, the main idea is quite simple - to quantify the magnitude of the observed deviation from the null hypothesis.

Examples of effect size estimators include the simple point estimator for the difference  $\bar{x} - \mu_0$ , or the dimensionless  $d$  estimator:

$$d = \frac{\bar{x} - \mu_0}{s}$$

which quantifies the difference in terms of sample standard deviations.

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<sup>c</sup>See, for instance, Paul D. Ellis' *The Essential Guide to Effect Sizes*, Cambridge University Press, 2010.

# Hypothesis Testing

p-values, effects sizes and confidence intervals



*Point estimators + confidence intervals quantify the magnitude and accuracy of effects, and must be reported alongside the results of significance testing whenever possible.*

Suppose we are testing  $H_0 : \mu = 50$  against the two-sided alternative hypothesis, with  $n = 10$  and  $\alpha = 0.01$ . Assume that the population is known to be Normal, with unknown variance. We'll use the same data as before:

```
> t.test(my.sample, mu = 50, conf.level = 0.99)
(...)
t = -1.5969, df = 9, p-value = 0.1447
alternative hypothesis: true mean is not equal to 50
99 percent confidence interval:
 48.93166 50.36434
sample estimates:
mean of x
 49.648
```

# Sample size and Type-II error

## Some considerations

The probability of Type-II error can be easily (and often wrongly) evaluated *a posteriori*, but its definition *a priori* requires some care;

Given a desired test, its power is essentially a function of 4 elements:

- Actual size of the difference;
- Variability of the observations;
- Significance level;
- Sample size.

The experimenter generally has very little control over the first two.

# Sample size and Type-II error

## Some considerations

A strategy for estimating an effective lower bound for the power of a test includes a definition of an *minimally interesting effect*  $\delta^*$ .

This value must be derived from technical and scientific knowledge about the phenomenon or system under experimentation.

It is essential to have a good understanding of the field in which the experiment will be conducted.

Once  $\delta^*$  is defined, the experimenter can obtain an estimate of the variability of observations (e.g., by a pilot study), which can then be used to obtain an approximate power value for the experiment;

# Sample size and Type-II error

## Some considerations

Having obtained this estimation of the Type-II error probability, one can run his/her experiment with a better understanding of its ability to detect effects of interest.

The test will have lower power for differences smaller than  $\delta^*$ , but these differences are below the minimally interesting effect; any effect greater than  $\delta^*$  will result in a higher power for the test;

This technique is most useful to compute the required sample size for the experiment.

## Sample size and Type-II error



## Example

Suppose that on the green peas example we are really interested in detecting negative deviations from the nominal value greater than 1%, i.e.,  $\delta^* = 0.01 \times 50 = 0.5\text{kg}$ . The researcher defines that, for this minimally interesting effect, a test power of 0.85 is desired. The desired significance is  $\alpha = 0.01$ .

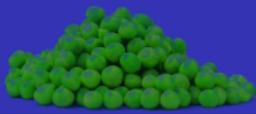
The same sample of  $n = 10$  sacks is used. Assume that a reasonable upper bound for the standard deviation can be estimated as  $\sigma = 1\text{kg}$ . From this data, we can compute the power of this test as:

```
> power.t.test(n = 10,  
+               delta = 0.5,  
+               sd = 1,  
+               sig.level = 0.01,  
+               type = "one.sample",  
+               alternative = "one.sided")
```

One-sample t test power calculation  
n = 10  
delta = 0.5  
sd = 1  
sig.level = 0.01  
power = 0.1654013 ←  
alternative = one.sided

# Sample size and Type-II error

Example



What is the smallest sample size needed to obtain the desired power of 0.85?

```
> power.t.test(power = 0.85, delta = 0.5, sd = 1, sig.level = 0.01,  
    type = "one.sample", alternative = "one.sided")
```

One-sample t test power calculation

n = 47.98044 ← (round this value up)

delta = 0.5

sd = 1

sig.level = 0.01

power = 0.85

alternative = one.sided

We need at least 48 observations to detect a  $-0.5\text{kg}$  (1%) or larger deviation on the mean weight of the green peas packages with a power level of 0.85.

# Model validation

## The normality assumption

The assumption of normality, required for the **z** and **t** tests, needs to be validated.

*“The Assumption of Normality (note the upper case) that underlies parametric stats does not assert that the observations within a given sample are normally distributed, nor does it assert that the values within the population (from which the sample was taken) are Normal. This core element of the Assumption of Normality asserts that **the distribution of sample means (across independent samples) is Normal.**”*

– J. Toby Mordkoff, 2011.<sup>(a)</sup>

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<sup>(a)</sup> Check J.T. Mordkoff's *The assumption(s) of normality* for a nice discussion on this topic: <http://goo.gl/z3w8ku>

# Model validation

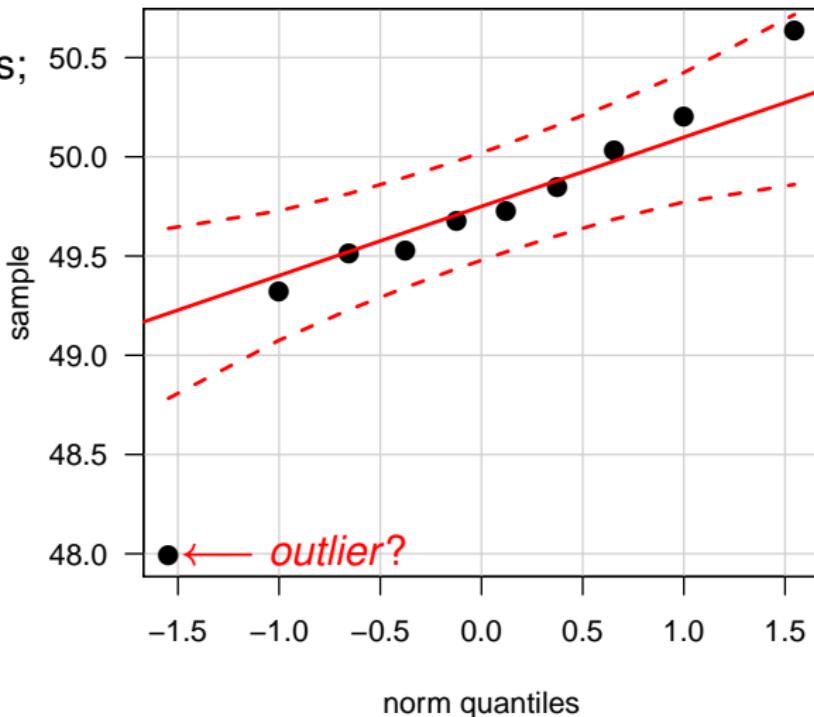
## The normality assumption



If the conditions for the CLT cannot be assumed *a priori*, then normality tests can be performed on the data.

### Graphical/qualitative tests;

```
> library(car)
> qqPlot(my.sample,
+         pch=16,
+         cex=1.5,
+         las=1)
```



# Model validation

## The normality assumption

Analytical tests of normality (choose **one**);

- Shapiro-Wilk;
- Anderson-Darling;
- Lilliefors / Kolmogorov-Smirnov;

These procedures use different aspects of the sample distribution to test the following hypotheses:

$$\begin{cases} H_0 : \text{population is Normal} \\ H_1 : \text{population is not Normal} \end{cases}$$

In this case, rejection of the null hypothesis suggests evidence that the **sample** came from a non-Normal population. Generally we use a strict  $\alpha$  threshold for these tests, and consider their results together with a graphical analysis.

# Model validation

## The normality assumption



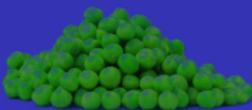
Even though the Lilliefors / Kolmogorov-Smirnov test is possibly the most widely used for normality testing, the Shapiro-Wilk test is recommended as a better alternative in Michael Crawley's *The R Book*, and will be used throughout this course.

```
> shapiro.test(my.sample)

Shapiro-Wilk normality test
data: my.sample
W = 0.8809, p-value = 0.1335
```

# Model validation

## The independence assumption



Possibly the strongest assumption of the statistical model used for the t-test is that of independence, that is, of the absence of unmodeled biases contaminating the data.

While I know of no procedure to test independence in the general case, the special case of serial autocorrelations in the data (which can emerge, for instance, as a consequence of heating effects or equipment degradation) can be tested by a procedure known as the Durbin-Watson test:

```
> library(car)
> durbinWatsonTest(lm(my.sample ~ 1))

lag Autocorrelation D-W Statistic p-value
1      -0.0848535     2.111733    0.898
Alternative hypothesis: rho != 0
```

# Model validation

## The independence assumption

The Durbin-Watson test depends on the ordering of the data, so observations should be ordered (either in the data file or by manipulating the data vector) according to covariates that are suspected to introduce dependencies, e.g., order of collection, placement criteria, etc.

Violations of the independence assumption tend to be the hardest to weed out, so extra care is recommended in the design of the experiment in order to prevent, control, or at least document all variables that could introduce dependencies in the data.

# The green peas experiment

Going over the process



After examining the green peas example, it is interesting to go back and follow the recommended sequence for this kind of experiment:

- Formulate question of interest;
- Define minimally interesting effect;
- Define desired confidence and power;
- Calculate required sample size;
- Collect data;
- Perform statistical analysis;
- Draw conclusions and recommendations.

# Bibliography

## Required reading

- ① D.C. Montgomery, G.C. Runger, *Applied Statistics and Probability for Engineers*, Ch. 9. 5th ed., Wiley, 2010.
- ② J.T. Mordkoff (2011), *The assumption(s) of normality* - <http://goo.gl/Z3w8ku>

## Recommended reading

- ① A. Reinhart, *Statistics Done Wrong: the woefully complete guide*. No Starch Press, 2015 (<http://www.statisticsonewrong.com>)
- ② W. Thalheimer and S. Cook, *How to calculate effect sizes from published research articles: A simplified methodology* - <http://goo.gl/c0g1oK>
- ③ E. Ernst and S. Singh, *Trick or Treatment*, Norton & Company, 2009.

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