Statistics: Changes since I was an undergrad

Part 2: Advances in theory and methods

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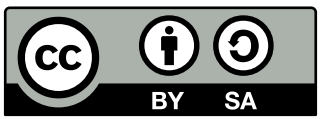

Lectures in this series

Changes in statistics: 1975–2014

This lecture is the second in a series of four related lectures.

1. Computing capacity has dramatically increased and programming languages have evolved.
2. New statistical methods have been developed.
3. Statistical software is dramatically more powerful and varied.
4. Accountability has become a requirement in scientific research.

Outline

Statistics

- Statistics is **not** an exact science.
- Different methods make different assumptions about the data.
- Different methods give different results ⇒ conclusions may depend on method.
- Selecting the method used is a key step in any analysis and assumptions play an important role when we choose a method.
- The number of methods to choose from has increased enormously in the last 35 years. (I started my university studies in 1975).
- This talk has two objectives: to familiarize you with general families of methods that have become usable on personal computers during this time.
- To highlight that some things that we frequently do, are just workarounds or kludges that are no longer needed.

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- Where did the risk levels (α) 10%, 5%, 1%, and 0.1% originate?
- Probabilities from the Normal and other distributions are not easy to calculate by hand. It became easy and fast to do so on the desktop around 1980s.
- Before 1990's we almost always reported P-values based on where the calculated t-value or F-value fell on a printed table. Interpolating to approximate the actual P-value was time consuming, and most researchers did not do it.

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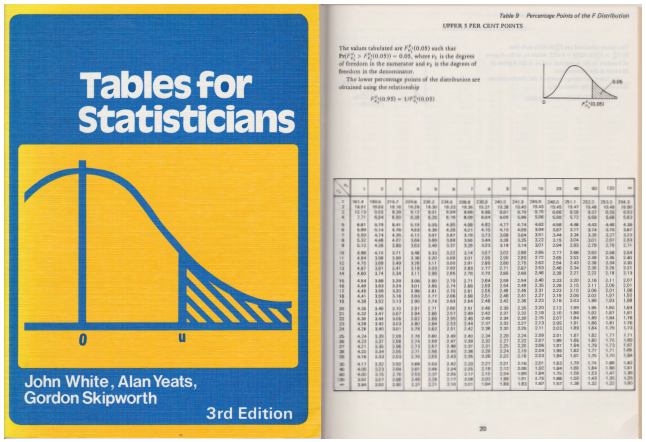
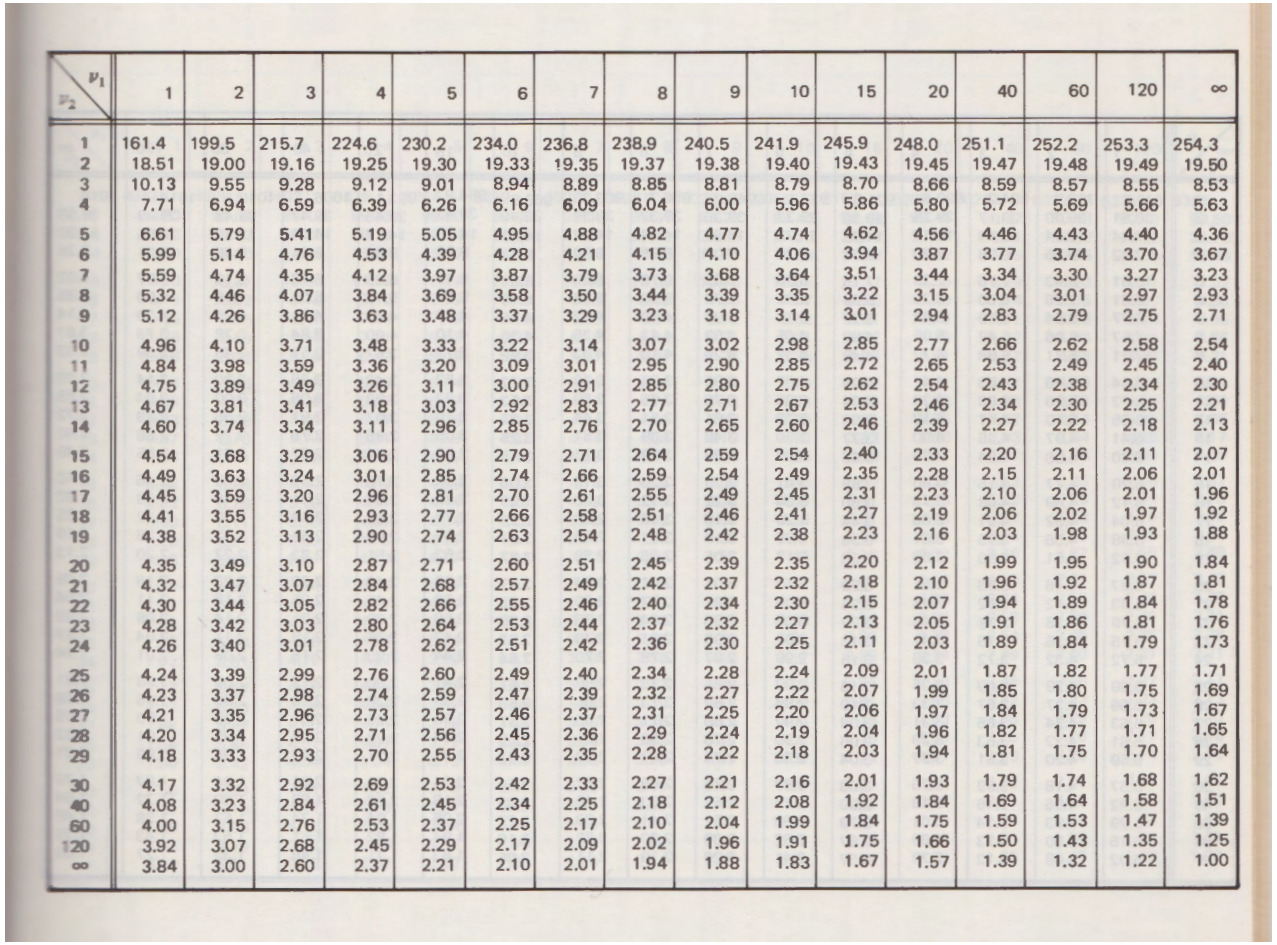


Tabulated values for $F_{\nu_2}^{\nu_1}(0.05)$



ν_2 \ ν_1	1	2	3	4	5	6	7	8	9	10	15	20	40	60	120	∞
1	161.4	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	245.9	248.0	251.1	252.2	253.3	254.3
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.43	19.45	19.47	19.48	19.49	19.50
3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.79	8.70	8.66	8.59	8.57	8.55	8.53
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.86	5.80	5.72	5.69	5.66	5.63
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.62	4.56	4.46	4.43	4.40	4.36
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	3.94	3.87	3.77	3.74	3.70	3.67
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.51	3.44	3.34	3.30	3.27	3.23
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.22	3.15	3.04	3.01	2.97	2.93
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.01	2.94	2.83	2.79	2.75	2.71
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.85	2.77	2.66	2.62	2.58	2.54
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.85	2.72	2.65	2.53	2.49	2.45	2.40
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.62	2.54	2.43	2.38	2.34	2.30
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.67	2.53	2.46	2.34	2.30	2.25	2.21
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.60	2.46	2.39	2.27	2.22	2.18	2.13
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.40	2.33	2.20	2.16	2.11	2.07
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.49	2.35	2.28	2.15	2.11	2.06	2.01
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	2.45	2.31	2.23	2.10	2.06	2.01	1.96
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	2.41	2.27	2.19	2.06	2.02	1.97	1.92
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	2.38	2.23	2.16	2.03	1.98	1.93	1.88
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.20	2.12	1.99	1.95	1.90	1.84
21	4.32	3.47	3.07	2.84	2.68	2.57	2.49	2.42	2.37	2.32	2.18	2.10	1.96	1.92	1.87	1.81
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34	2.30	2.15	2.07	1.94	1.89	1.84	1.78
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32	2.27	2.13	2.05	1.91	1.86	1.81	1.76
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30	2.25	2.11	2.03	1.89	1.84	1.79	1.73
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.09	2.01	1.87	1.82	1.77	1.71
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.27	2.22	2.07	1.99	1.85	1.80	1.75	1.69
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40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	1.92	1.84	1.69	1.64	1.58	1.51
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04	1.99	1.84	1.75	1.59	1.53	1.47	1.39
120	3.92	3.07	2.68	2.45	2.29	2.17	2.09	2.02	1.96	1.91	1.75	1.66	1.50	1.43	1.35	1.25
∞	3.84	3.00	2.60	2.37	2.21	2.10	2.01	1.94	1.88	1.83	1.67	1.57	1.39	1.32	1.22	1.00

Risk levels

Problem

Reporting $P < 0.05$ for both $P = 0.049$ and $P = 0.011$ discards important information.

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Reporting an effect as significant when $P = 0.048$ and not significant when $P = 0.051$ without further details is misleading.

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Adjusting P-values

Bonferroni's method

Bonferroni's correction is very simple, and easy to calculate

$$\alpha_{\text{adj}} = \frac{\alpha}{n}$$

where α is the 'risk level' and n the number of contrasts.

Problem

But is extremely conservative! $\Rightarrow$ tests have low power (too low sensitivity to real treatment effects).

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LSD is very easy to calculate but ignores simultaneous testing (like trying to get a given value by rolling a die several times).

Recommendation

Never use LSD (least significant difference) for multiple comparisons.

Solution

Keep the number of tests to the minimum (decide *a priori* which ones are most interesting) and use a modern and well-behaved for adjusting P-values.

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Types of "fitted" functions

- Functions linear in the parameters: e.g. polynomials.

$$y = a_0 + a_1 \cdot x + a_2 \cdot x^2 + a_3 \cdot x^3$$

  Exact analytical methods, but with strict assumptions.
- Functions not linear in the parameters: e.g. exponential.

$$y = a_0 + \mathrm{e}^{a_1 \cdot x}$$

  Approximate iterative numerical methods.
- Splines (piece-wise functions): e.g. cubic splines.
  Approximate iterative numerical methods.

Models linear in the parameters

- Using iterative methods was almost impossible early on,
  1) because of the time needed for repeated calculation, and
  2) when using slide rules and the like, accumulation or errors.
- Using analytical solutions to least squares fits of linear models could be calculated already more than 200 years ago, if strict assumptions on data properties where adopted.
- When the assumptions did not hold, we had to modify the data using **transformations**.
- Nowadays we can easily fit non-linear and linear mixed models, and also additive models, assuming different distributions, or even not assuming any specific shape for the distribution. Many other assumptions can also be relaxed, even if we do calculations on a desktop or laptop computer.

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When to use data transformations

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In a factorial ANOVA the use of transformations changes the interpretation of interactions and additivity of effects. H_0 for untransformed data: additive effects, but for log transformed data: multiplicative effects on original scale.

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Choosing models: LM

- Linear models should be familiar to all of you.
- They include linear and polynomial regression, ANOVA and ANCOVA.
- They can be fitted using least squares as the optimization criterium using an exact analytical method.
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- We can specify the distribution that is assumed (e.g. Poisson, Binomial, etc.) and the link function (e.g. log or linear). This makes it possible to analyse count and frequency data directly, without need for transformations or special handling of zeros.
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Choosing models: GLS, LME and GLMM

- Nowadays it is relatively easy to fit LME (linear mixed effects) models, GLS (general linear) models, and somehow more difficult to fit GLMM (generalized linear mixed) models.
- In all these models the error variance can be estimated based on variance covariates, variance structures, and correlations (including auto-correlations).
- Mixed effects models allow for partitioning of the random variation into (nested) components (e.g. those corresponding to blocks and plants).
- Fitting is by approximate iterative methods, but although methods frequently converge to a good answer, one should check for non-convergence. Estimates of degrees of freedom are approximations, consequently so are P-values.
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The good and the bad

The models to choose from are many. This is good, but it makes model selection a key and rather time-consuming step in the analysis.

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We are interested in RGR (relative growth rate), then fitting a NLME to log-transformed dry-weight data may be best.

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Statistics and the research process

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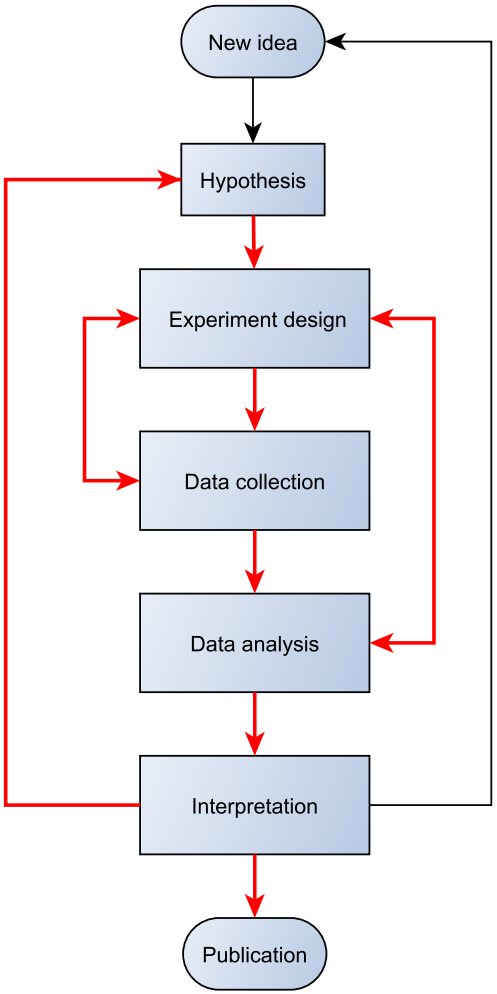
Flowchart: statistics and research process



Recommendations on design

- Design your experiment taking into account how the data could be analysed, and considering the different alternatives available.
- Design your experiment so that you maximize the chances of reliably testing the hypothesis of interest.
- Things to consider during the design phase include size of response that should be detectable, expected amount and type of random variation, possible confounding sources of variation, ways of minimizing the unaccounted variation, and of improving the estimates of the parameters that are most interesting.
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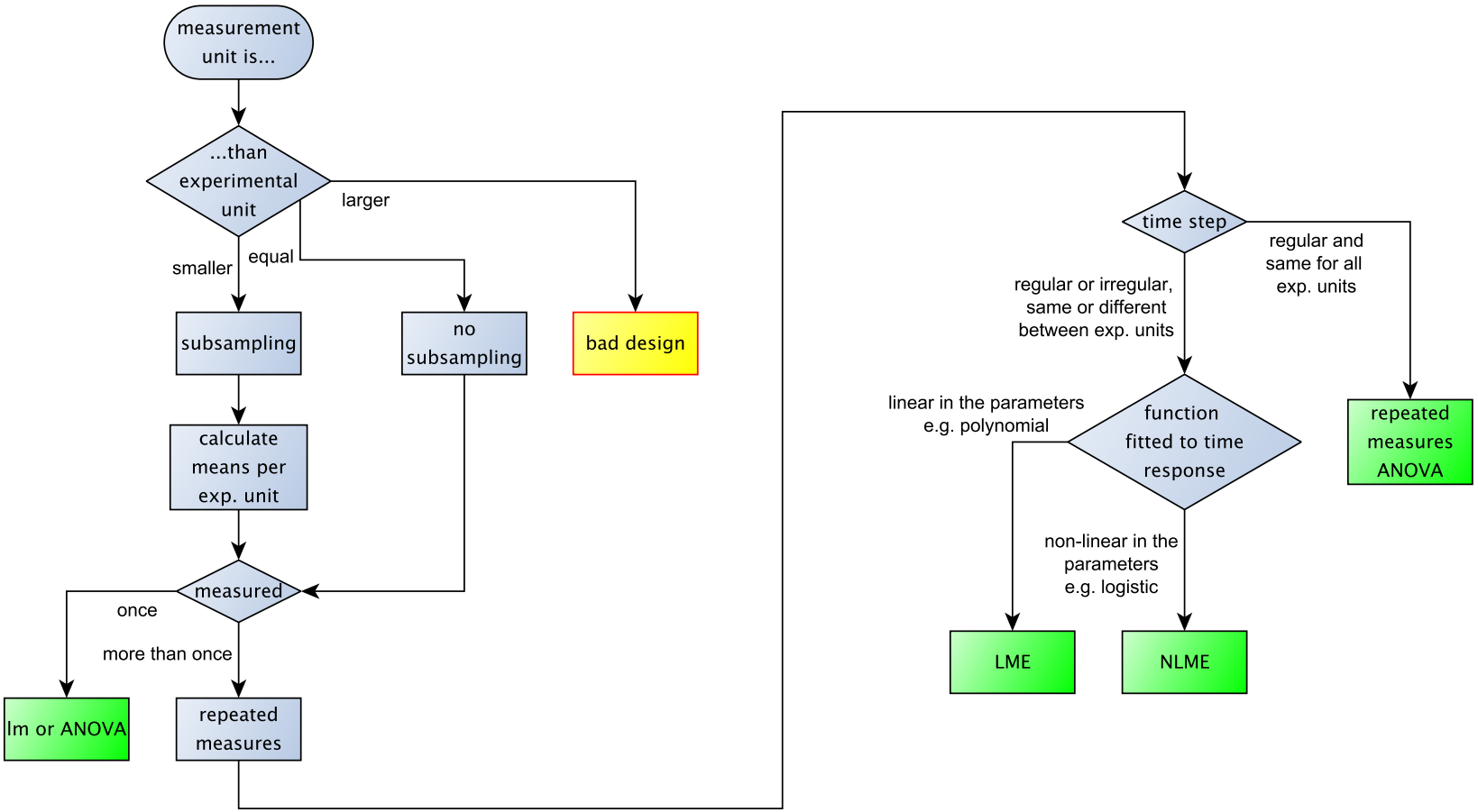
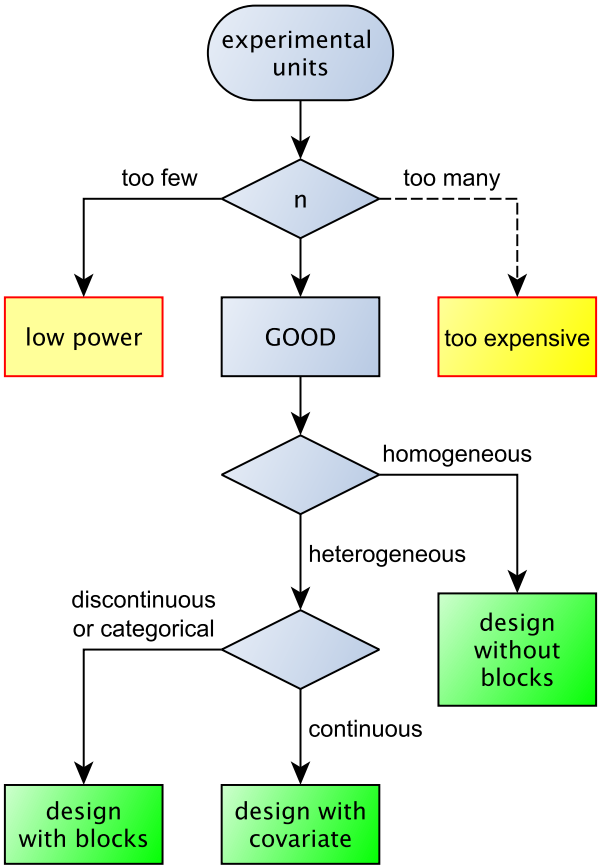
Concept: experimental vs. measurement units

- A correct statistical analysis is only possible if we correctly identify the true experimental units in our experiments.
- First step when analysing data is to make sure that the model used matches the replication used.
- An *experimental unit* is the unit or 'thing' to which the treatment is assigned (at random) (e.g. a plant in a pot).
- An experimental unit is not necessarily the unit that is measured, which can be smaller (e.g. a leaf from the treated plant ⇒ measuring several leaves separately does not increase the number of replicates).
- A measured object (= measurement unit) which is smaller than an experimental unit is called a sub-sample.

Flowchart: experimental vs. measurement units



Flowchart: replication



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- Think twice before using transformations of your data.
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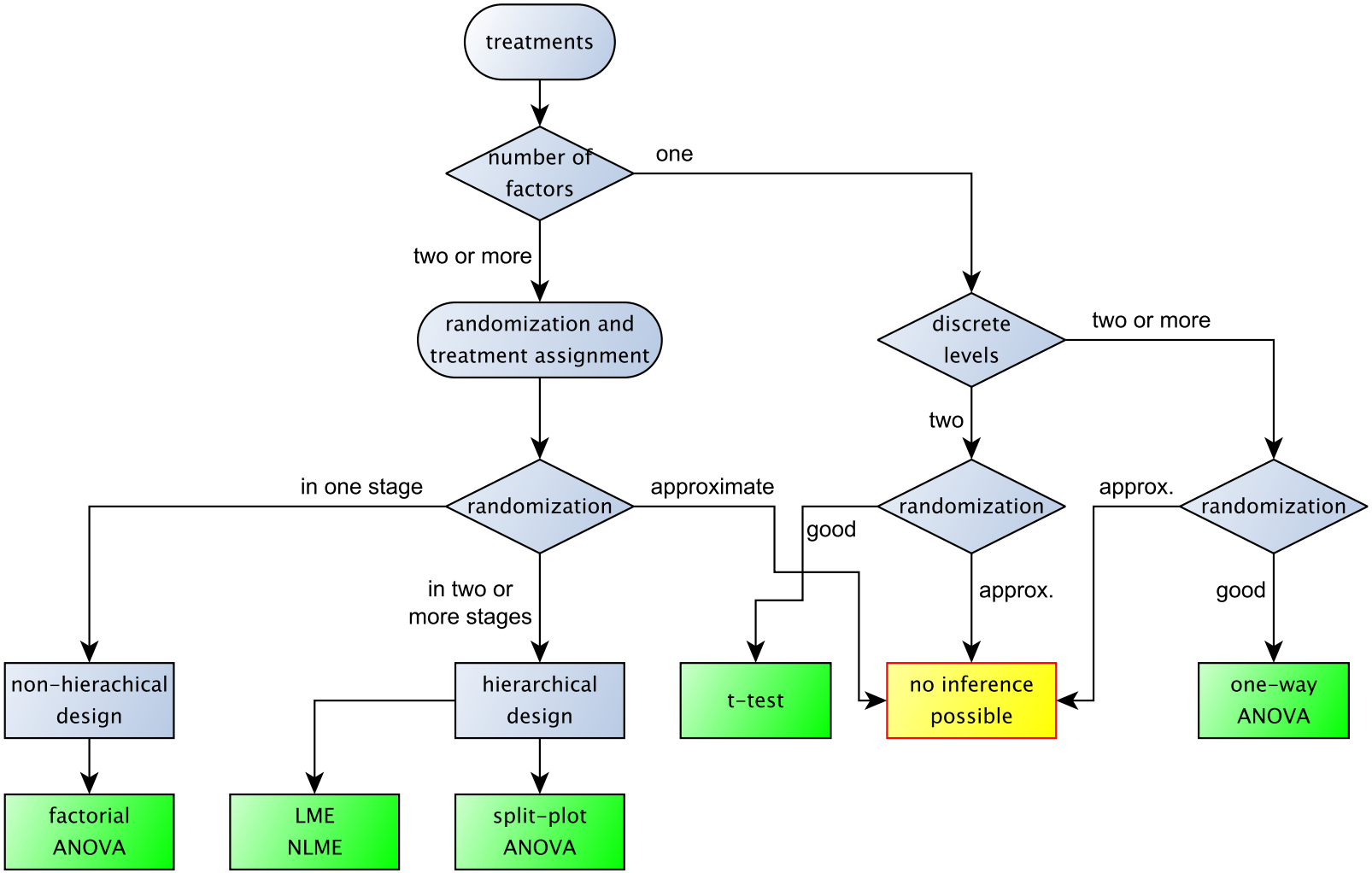
Flowchart: choosing the statistical model



The End

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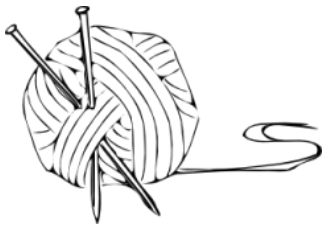

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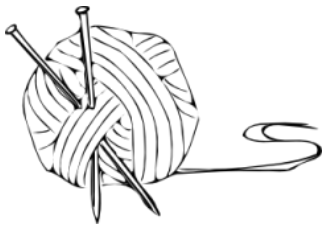

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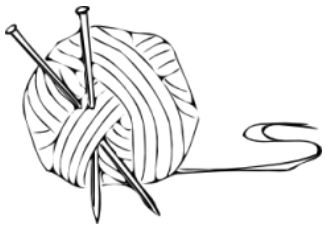

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