SAGE researchmethods

Last Observation Carried Forward

In: Encyclopedia of Research Design

By: David L. Streiner
Edited by: Neil J. Salkind
Book Title: Encyclopedia of Research Design
Chapter Title: "Last Observation Carried Forward"
Pub. Date: 2012
Access Date: January 1, 2021
Publishing Company: SAGE Publications, Inc.
City: Thousand Oaks
Print ISBN: 9781412961271
Online ISBN: 9781412961288
DOI: https://dx.doi.org/10.4135/9781412961288
Print pages: 687-688
© 2010 SAGE Publications, Inc. All Rights Reserved.
This PDF has been generated from SAGE Research Methods. Please note that the pagination of the online version will vary from the pagination of the print book.

2010 SAGE Publications, Ltd. All Rights Reserved.

Last observation carried forward (LOCF) is a method of imputing missing data in longitudinal studies. If a person drops out of a study before it ends, then his or her last observed score on the dependent variable is used for all subsequent (i.e., missing) observation points. LOCF is used to maintain the sample size and to reduce the bias caused by the attrition of participants in a study. This entry examines the rationale for, problems associated with, and alternative to LOCF.

Rationale

When participants drop out of longitudinal studies (i.e., ones that collect data at two or more time points), two different problems are introduced. First, the sample size of the study is reduced, which might decrease the power of the study, that is, its ability to detect a difference between groups when one actually exists. This problem is relatively easy to overcome by initially enrolling more participants than are actually needed to achieve a desired level of power, although this might result in extra cost and time. The second problem is a more serious one, and it is predicated on the belief that people do not drop out of studies for trivial reasons. Patients in trials of a therapy might stop coming for return visits if they feel they have improved and do not recognize any further benefit to themselves from continuing their participation. More often, however, participants drop out because they do not experience any improvement in their condition, or they find the side effects of the treatment to be more troubling than they are willing to tolerate. At the extreme, the patients might not be available because they have died, either because their condition worsened or, in rare cases, because the “treatment” actually proved to be fatal. Thus, those who remain in the trial and whose data are analyzed at the end reflect a biased subset of all those who were enrolled. Compounding the difficulty, the participants might drop out of the experimental and comparison groups at different rates, which biases the results even more.

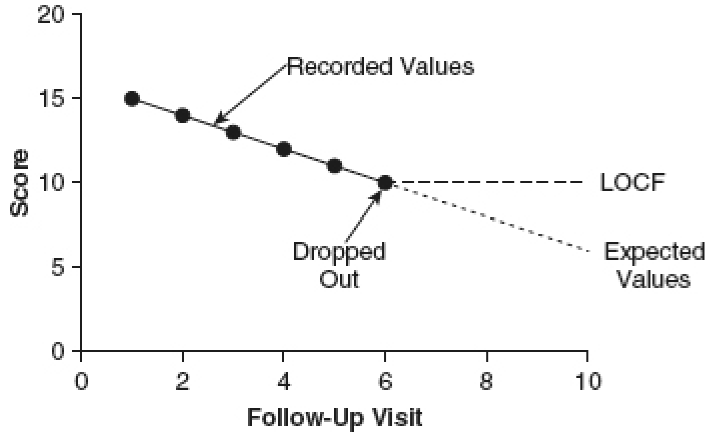
Needless to say, the longer the trial and the more follow-up visits or interviews that are required, the worse the problem of attrition becomes. In some clinical trials, drop-out rates approach 50% of those who began the study.

LOCF is a method of data imputation, or “filling in the blanks,” for data that are missing because of attrition. This allows the data for all participants to be used, ostensibly solving the two problems of reduced sample size and biased results. The method is quite simple, and consists of replacing all missing values of the dependent variable with the last value that was recorded for that particular participant. The justification for using this technique is shown in Figure 1, where the left axis represents symptoms, and lower scores are better. If the effect of the treatment is to reduce symptoms, then LOCF assumes that the person will not improve any more after dropping out of the trial. Indeed, if the person discontinues very early, then there might not be any improvement noted at all. This most probably underestimates the actual degree of improvement experienced by the patient and, thus, is a conservative bias; that is, it works against the hypothesis that the intervention works. If the findings of the study are that the treatment does work, then the researcher can be even more confident of the results. The same logic applies if the goal of treatment is to increase the score on some scale;

2010 SAGE Publications, Ltd. All Rights Reserved.

LOCF carries forward a smaller improvement.

Figure 1 The Rationale for Last Observation Carried Forward



Problems

Counterbalancing these advantages of LOCF are several disadvantages. First, because all the missing values for an individual are replaced with the same number, the within-subject variability is artificially reduced. In turn, this reduces the estimate of the error and, because the within-person error contributes to the denominator of any statistical test, it increases the likelihood of finding significance. Thus, rather than being conservative, LOCF actually might have a liberal bias and might lead to erroneously significant results.

Second, just as LOCF assumes no additional improvement for patients in the treatment condition, it also assumes that those in the comparison group will not change after they drop out of the trial. However, for many conditions, there is a very powerful placebo effect. In trials involving patients suffering from depression, up to 40% of those in the placebo arm of the study show significant improvement; and in studies of pain, this effect can be even stronger. Consequently, in underestimating the amount of change in the control group, LOCF again might have a positive bias, favoring rejection of the null hypothesis.

Finally, LOCF should never be used when the purpose of the intervention is to slow the rate of decline. For example, the so-called memory-enhancing drugs slow the rate of memory loss for patients suffering from mild or moderate dementia. In Figure 1, the left axis would now represent memory functioning, and thus lower scores are worse. If a person drops out of the study, then LOCF assumes no additional loss of functioning, which biases the results in favor of the treatment. In fact, the more people who drop out of the study, and the earlier the drop-outs occur, the better the drug looks. Consequently, LOCF introduces a very strong liberal bias, which significantly overestimates the effectiveness of the drug.

Alternatives

Fortunately, there are alternatives to LOCF. The most powerful is called growth curve analysis (also known

2010 SAGE Publications, Ltd. All Rights Reserved.

as latent growth modeling, latent curve analysis, mixed-effects regression, hierarchical linear regression, and about half a dozen other names), which can be used for all people who have at least three data points. In essence, a regression line is fitted to each person's data, and the slope and intercept of the line become the predictor variables in another regression. This allows one to determine whether the average slope of the line differs between groups. This does not preserve as many cases as LOCF, because those who drop out with fewer than three data points cannot be analyzed, but latent growth modeling does not introduce the same biases as does LOCF.

David L. Streiner

http://dx.doi.org/10.4135/9781412961288.n211

See also

- Bias
- Latent Growth Modeling
- Missing Data, Imputation of

Further Readings

Molnar, F. J. , Hutton, B. , & Fergusson, D. *Does analysis using “last observation carried forward” introduce bias in dementia research?* (2008).179,751–753.

Singer, J. D., &Willett, J. B.(2003). Applied longitudinal data analysis: Modeling change and event occurrence.New York: Oxford University Press.