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Cairo University
Faculty of Economics and Political Science
Department of Statistics

**Analysis of Longitudinal data with intermittent Missing Values
Using the Stochastic EM Algorithm**

373.08

By

Abeer Saleh Ahmed Abd-Alla

Supervised by

Professor Dr. Maged Osman
Professor of Statistics
Faculty of Economics and Political Science
Cairo University



Dr. Laila El-Zeini
Associate Professor of Statistics
Faculty of Economics and Political Science
Cairo University



A Thesis Submitted to the Faculty of Economics and Political Science (Department of Statistics) in partial Fulfillment of the Requirements for the Ph. D. in Statistics

2005



بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

وَمَا أُوتِيتُمْ مِنَ الْعِلْمِ إِلَّا قَلِيلًا

صَدَقَ
الْعَظِيمُ



DEDICATION



Abeer, Yasmeen, Dr. Ahmed Gad and My Family

Name: Abeer saleh ahmed Abd-Alla

Nationality: Egyptian

Date and Place of birth: 29/6/ Cairo

Degree: Ph.D.

Specialization: Statistics

Supervisors:

Professor Dr. Maged Osman

Professor of Statistics

Dr. Laila El-Zeini

Associate Professor of Statistics

Title of the Thesis: "Analysis of Longitudinal Data with Intermittent Missing Values using The Stochastic EM Algorithm"

Summary:

In longitudinal studies each unit is measured on several occasions. In practice, some intended measurements may not be available for some subjects resulting in a missing data pattern. Dropout pattern occurs when some subject are withdrawn from the study prematurely. The missing data pattern is defined as intermittent if a missing value is followed by an observed value. When the probability of missingness depends on the missing value, and may be on the observed values, the missing data mechanism is termed as nonrandom. Ignoring the missing values mechanism in this case leads to biased inference. In this study, the stochastic EM algorithm is proposed and developed to find parameters estimates to normal response distribution in the presence of intermittent missing values. Also, in this setting, the Monte Carlo method is developed to find the standard errors of parameters estimates. Assumptions about the distribution of the response can have a large effect on inference about parameters that govern the dropout process. So, it is important to consider the sensitivity of conclusions to distributional assumptions. We apply the proposed method to non-normal response distribution. This enables us to examine the effect of the distributional assumptions of the response on the parameters that characterize the dropout process. Finally, the proposed techniques are applied to a real data from the International Breast Cancer Study Group.

Supervisors:

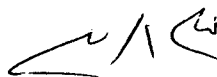
Professor Dr. Maged Osman

Professor of Statistics



Dr. Laila El-Zeini

Associate Professor of Statistics



Abstract

In longitudinal studies each unit is measured on several occasions. In practice, some intended measurements may not be available for some subjects resulting in a missing data pattern. Dropout pattern occurs when some subject are withdrawn from the study prematurely. The missing data pattern is defined as intermittent if a missing value is followed by an observed value. When the probability of missingness depends on the missing value, and may be on the observed values, the missing data mechanism termed as nonrandom. Ignoring the missing values mechanism in this case leads to biased inference. In this study, the stochastic EM algorithm is proposed and developed to find parameters estimates to normal response distribution in the presence of intermittent missing values. Also, in this setting, the Monte Carlo method is developed to find the standard errors of parameters estimates. Assumptions about the distribution of the response can have a large effect on inference about parameters that govern the dropout process. So, it is important to consider the sensitivity of conclusions to distributional assumptions. We apply the proposed method to non-normal response distributions. This enables us to examine the effect of the distributional assumptions of the response on the parameters that characterize the dropout process. Finally, the proposed techniques are applied to a real data from the International Breast Cancer Study Group.

Key words: Longitudinal data; Nonrandom missing values; Intermittent missing data; The stochastic EM algorithm; MCMC methods; Standard errors.

Supervisors:

Professor Dr. Maged Osman

Professor of Statistics



Dr. Laila El-Zeini

Associate Professor of Statistics



Acknowledgements

First of all, ultimate thanks are due to ALLAH. Many thanks to my mother who without her aid this work could not be done.

I wish to express my sincere appreciation and gratefulness to Dr. Ahmed M. Gad, Department of Statistics, Faculty of Economics and Political Science, Cairo University for suggesting this point for research, supervising, valuable help and constructive criticism. His effort in revising the manuscript is much appreciated.

Deep thanks and gratitude are also due to Prof. Dr. Maged Osman, professor of statistics, Department of Statistics, Faculty of Economics and Political Science, Cairo University for supervising.

Thanks are also extended to Dr. Laila El-Zeini, associate professor of statistics, Department of Statistics, Faculty of Economics and Political Science, Cairo University for sharing the supervision.

I would like to thank Quality of Life Committee of the International Breast Cancer Study Group for permission to use the quality-of-life data.

My sincerest thanks go to my family. My family has been a constant source of support, emotional and moral, during my preparation for this thesis.

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