School of Electrical Engineering, Computing and
Mathematical Sciences

Centre for Transforming Maintenance Through Data Science

Practical Bayesian model building for reliability analysis in industry settings.

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This thesis is presented for the Degree of
Doctor of Philosophy
of
Curtin University of Technology

November 2023

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Ryan K. Leadbetter

"*The Quote*"

— AUTHOR

Acknowledgements

Write your acknowledgements here

Abstract

Write your abstract here

Contents

List of Figures

Chapter 1

Introduction: Bayesian reliability modelling

Introduction to reliability modelling and the theme of the thesis; which is reliability modelling in the 'real world'.

1.1 Asset health management?

Do I need to talk about replacement strategies?

1.2 Reliability modelling

General introduction to reliability data is SMRD2 Meeker, Escobar, and Pascual and a good bridge between lifetime data and degradation modelling is Bayesian Reliability Hamada, Wilson, Reese, and Martz.

Lifetime data Definition of lifetime analysis.

Degradation data Definition of degradation modelling.

1.3 Bayesian methods and workflow

An overview of Bayesian methods.

Probably also some discourse on the Bayesian workflow.

1.3.1 Simulation for model checking

An ongoing thread through the thesis is the concept of using simulated date from a known underlying truth to assess model performance...

1.4 Structure of this thesis

How parts and chapters are laid out.

Part I

Part one: lifetime analysis

A preamble about which chapters have been published and which chapters came from industry placements.

Chapter 2

Heavily censored lifetime data

Computerised maintenance management systems (CMMS) such as SAP SE (2023) are now embedded in companies maintenance procedures, meaning that these companies now posses large scale datasets of component installation and replacement times. A natural use of these personalised failure time data sets is for tailoring replacement strategies for the companies specific operating environments, rather than solely relying on the manufacturers recommendations. One problem however, is that these large observational datasets collected through CMMS are much messier that the experimental ones used by manufacturers in traditional reliability analysis. This messiness comes about because of reporting issues and the fact that most components are pre-emptively replaced before they fail because of the risk to production and employees safety. The result is that many of the valuable data sets stored in CMMS systems are heavily censored. In this chapter we. . .

2.1 Background

Lifetime analysis, also called survival analysis, is the analysis of failure time data of a particular type of unit to derive the risk of failure dependent on a specific exposure (usually some form of time) and sometimes other covariates (Smith, n.d.).

Analysis typically involves first formulating a sampling distribution by choosing some parametric lifetime distribution for the units and incorporating any observational characteristics of the data–for example censoring–then next, estimating the parters of the distribution from failure time data using an appropriate inferential mechanism, and finally using the fitted model to derive useful reliability measures about the population. When done in a Bayesian context, this process also included specifying a prior. From the derived data-informed outputs, we can devise optimal maintenance strategies.

2.1.1 Lifetime distribution

The Lifetime distribution is the distribution from which the failure times arise, i.e. it describe the probability of failure at a given exposure. In reliability, the exposure is typically absolute time or the operating time of the unit. Say we choose a specific parametric lifetime distribution for the population of units, $p(t|\theta)$ expressed as the probability density function (CDF). Once we have estimated the parameters of the lifetime distribution we can draw useful interpretation of the

- CDF (The probability that a unit will have failed by time T, i.e. $P(t <= T)$.)

- Hazard (The instantaneous failure rate at a given exposure.)

2.1.2 The Weibull distribution

Details of the Weibull.

2.1.3 Censoring

What is Censoring?

2.1.4 An example from industry

2.2 Bias in heavily censored lifetime data

Introduce the problem that, when data are heavily censored, the estimates of lifetime parameters become bias. We will show via simulated data so that the underlying truth is known.

2.2.1 Simulation method

How do we simulate censored lifetime data?

2.2.2 Bias in results

How does the estimated CDF differ from the truth?

2.3 Informative Bayesian analysis

How can informative priors help us in this case?

Independent Construction of independent priors.

Joint Construction of the joint prior.

2.3.1 Effect of informative priors

Compare the estimated CDF for the three different models with the truth.

2.4 Discussion

...

Chapter 3

Simulation study

Outline on structure of chapter and what I wish to achieve in the simulation experiment.

3.1 Simulation structure

How do we structure the simulation experiment? What are we testing?

3.2 Results

Visualise/summarise the results of the simulation experiment.

3.3 Discussion

Typical results section.

3.4 Recommendations

What are our recommendations for handling heavily censored data? (which we will implement in the next chapter)

Chapter 4

Case study

A case study.

4.1 Idler replacement data

4.2 Results

4.3 Discussion

Part II

Part two: Degradation modelling

A preamble about which chapters have been published and which chapters came from industry placements.

Chapter 5

Noisy gamma process for modelling degradation measurements with uncertainty

5.1 Background

5.1.1 BHM

5.1.2 Gamma process

5.1.3 Gamma process with noise

Chapter 6

Conveyor belt wear forecasting

6.1 Background

6.1.1 FDA

6.2 Process models

6.2.1 Linear

6.2.2 Noisy GP

Chapter 7

Conveyor belt wear forecast with spatial random effect

Chapter 8

Discussion

8.1 Tie together discussion

8.2 Strengths and limitations

8.3 Future directions

8.4 Industry practitioner implications

Appendices

Appendix A

Appendix Title

Appendix B

Copyright Information

References

SAP SE. (2023). *Sap software suite.* https://www.sap.com.

Smith, J. (n.d.).

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