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Distance models for analysis of multivariate binary data

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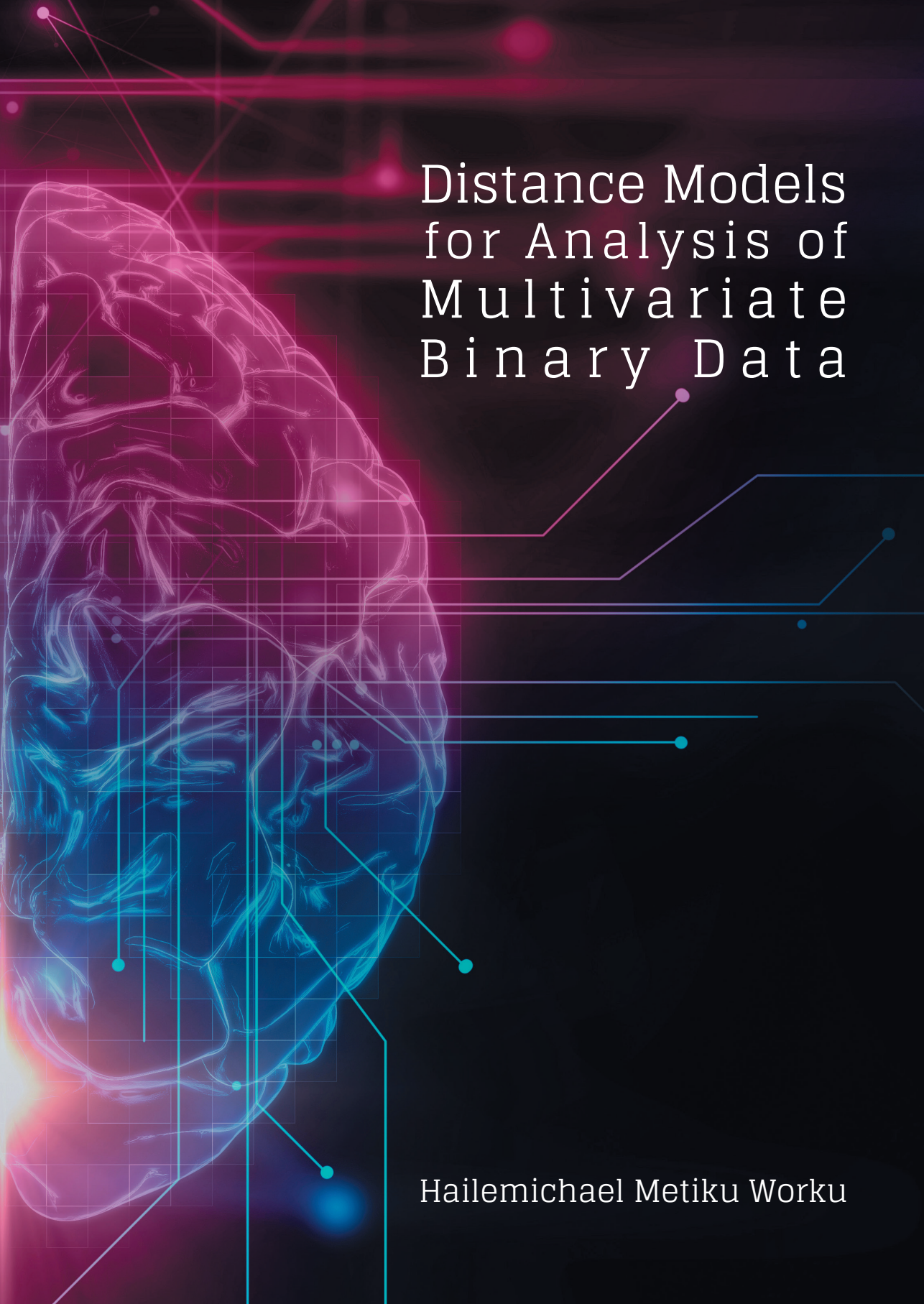
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The background features a stylized, glowing brain in shades of blue and purple, overlaid with a grid of white lines. Several bright, colorful lines (red, orange, yellow) radiate from the top left corner, creating a sense of dynamic energy and connectivity. The overall aesthetic is futuristic and technological.

Distance Models for Analysis of Multivariate Binary Data

Hailemichael Metiku Worku

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PROEFSCHRIFT

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Motto

⁷Though your beginnings were modest, your latter days will be full of
prosperity. (Job 8:7)

Research Articles

As presented below, the chapters of this dissertation are based on published (or to be submitted) articles.

- Chapter 3: Worku, H. M. & De Rooij, M. (2017). Properties of Ideal Point Classification Models for Bivariate Binary Data. *Psychometrika*, **82** (2), 308-328.
- Chapter 4: Worku, H. M. & De Rooij, M. (2018). A Multivariate Logistic Distance Model for the Analysis of Multiple Binary Responses. *Journal of Classification*, **35**, 1-23. <https://doi.org/10.1007/s00357-018-9251-4>
- Chapter 5: Worku, H. M. & De Rooij, M. **mldm**: An R package for Analyzing Multivariate Binary Data. The package can be retrieved from <https://github.com/workuhm1/mldm-package-github>.

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