

Machine Learning for Psychological Research: Benchmarking Forecasting Performance of Deep Learning Models for Longitudinal Data

Thursday 24 July 2025 10:15 (15 minutes)

Oral presentation

Machine Learning for Psychological Research: Benchmarking Forecasting Performance of Deep Learning Models for Longitudinal Data

Author

Nedderhoff, Andre

Affiliation

Helmut Schmidt University

Abstract

The study of longitudinal data has been a cornerstone of psychological research, shaped significantly by the foundational work of Baltes and Nesselroade (1979). With the rise of mobile IT tools, interest in modeling intensive longitudinal data has surged. Traditionally, psychologists have relied on time-series analysis methods such as the Random Intercept Cross-Lagged Panel Model (RI-CLPM) and continuous-time models to analyze (intensive) longitudinal data and examine temporal relationships between variables.

In recent years, advances in Machine Learning (ML) have opened new possibilities for analyzing longitudinal data, particularly in forecasting future values. Our study explores the potential of ML models for this purpose by simulating time series based on a discrete-time model, varying key design factors such as the number of input and forecasted time points, sample size, and temporal drift.

We evaluated these simulated time series using two established psychological models, the discrete time RI-CLPM (Hamaker & Grasman, 2015) and the continuous-time RI-CLPM (Oud & Delsing, 2010) - and compare their forecasting performance with two widely used ML models: Long Short-term memory networks (LSTM; Hochreiter & Schmidhuber, 1997) and Transformer neural networks (Vaswani et al., 2017). Our study assesses each model's forecasting capabilities in a univariate forecasting scenario, using bias and root mean square error (RMSE) as performance metrics.

References

Baltes, P. B., & Nesselroade, J. R. (1979). History and rationale of longitudinal research. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal Research in the Study of Behavior and Development* (pp. 1-39). Academic Press.

Hamaker, E. L., & Grasman, R. P. P. (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. *Frontiers in Psychology*, 5. <https://doi.org/10.3389/fpsyg.2014.01492>

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, 9(8), 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735>

Oud, J. H. L., & Delsing, M. J. M. H. (2010). Continuous Time Modeling of Panel Data by means of SEM. In K. Van Montfort, J. H. L. Oud, & A. Satorra (Eds.), *Longitudinal Research with Latent Variables* (S. 201–244). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-11760-2_7

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.

Keywords

forecasting, machine learning, sem, simulation

Primary author: NEDDERHOFF, Andre

Co-authors: HECHT, Martin; ZITZMANN, Steffen (MSH Medical School Hamburg)

Session Classification: Session 20: "IA y M learning"

Track Classification: Statistical analyses: Statistical analyses