WP4 Machine Learning

Manuel Brenner Daniel Durstewitz Peter Kuppens



This project has received funding from the European Union's Horizon 2020 research and innovation Programme under grant agreement 945263 (IMMERSE)

WP4 – Overview, objectives, and aims

- **4.1 Basic data characteristics, robust statistics, and visualization**
  - Implementation of robust low level statistics for DMMH

- **4.2 Machine learning for multimodal data integration**
  - Identify predictive behavioral contingencies for mental health
  - Identify optimal leveraging points for improving mental health

- **4.3 Development of efficient cross-site big data integration framework for multi-modal time series**
  - Establish a cross-site validated analysis tool which harvests the potential of big (time series) data to forecast individual health trajectories

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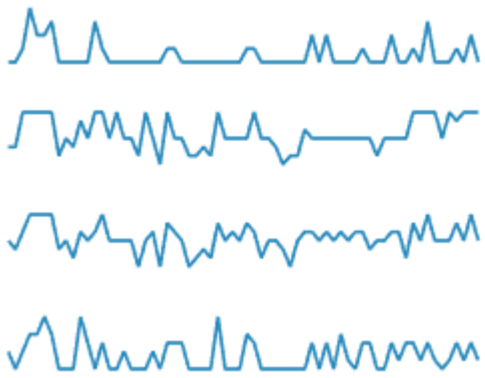
Task 4.2. Machine learning for multimodal data integration

Reconstructing dynamical systems via RNNs



observed

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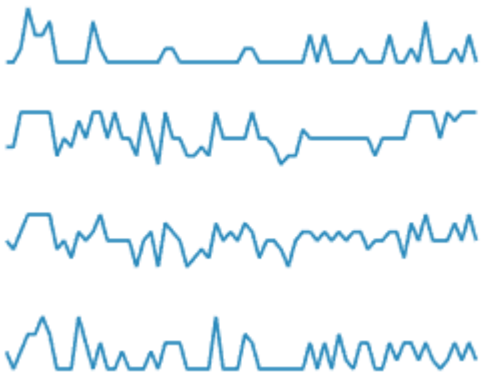
Task 4.2. Machine learning for multimodal data integration

Reconstructing dynamical systems via RNNs

dynamical system

$$\boldsymbol{x}_t = f_\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{\varepsilon}_t)$$



observed

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Task 4.2. Machine learning for multimodal data integration

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Reconstructing dynamical systems via RNNs

dynamical system

$$\boldsymbol{x}_t = f_\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{\varepsilon}_t)$$

$$\boldsymbol{y}_t = g_\lambda(\boldsymbol{x}_t, \boldsymbol{\eta}_t)$$

unobserved **observed**

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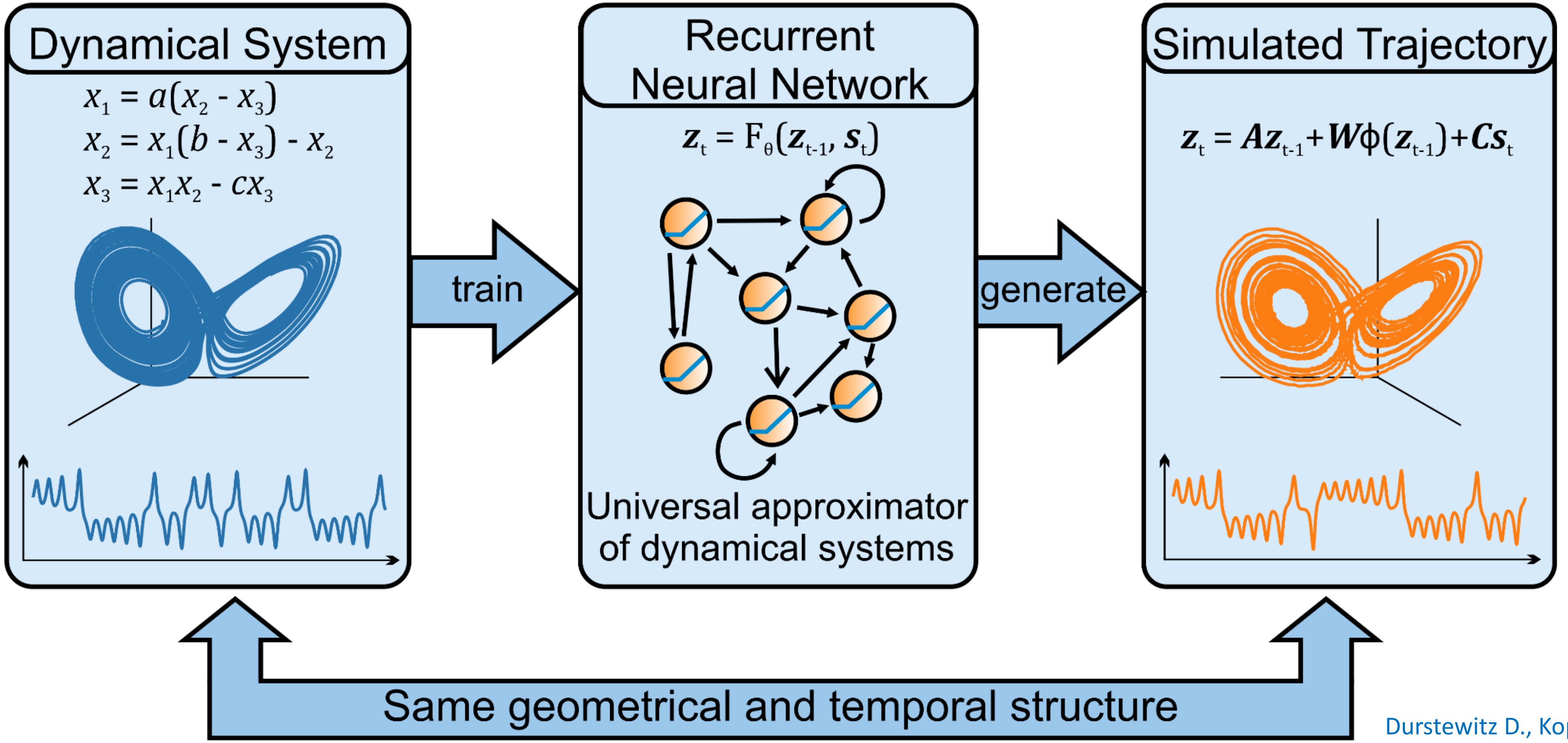

Durstewitz D., Koppe G.. Thurm, M.I. (2022). BioRxiv
Schmidt*, Koppe* et al (2020). ICLR
Koppe et al (2019). PLoS Comput Biol

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Examples in neuroscientific data

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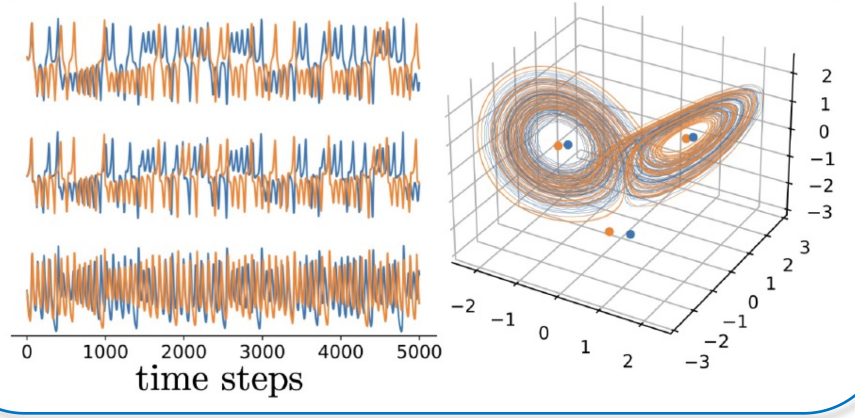
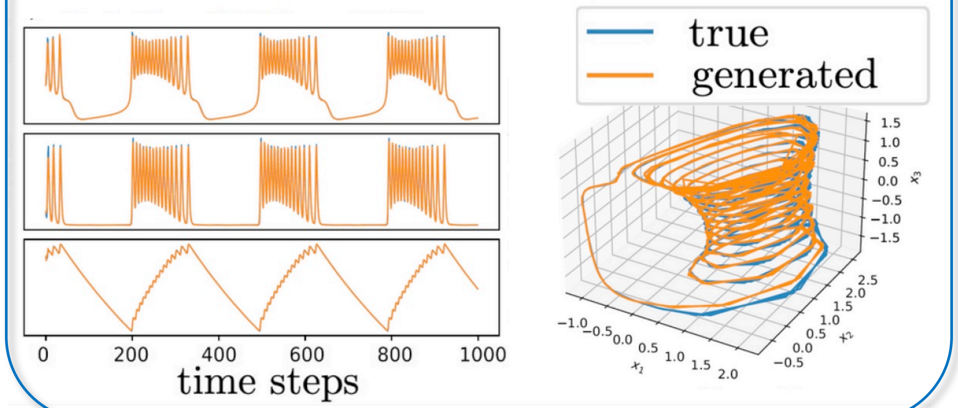
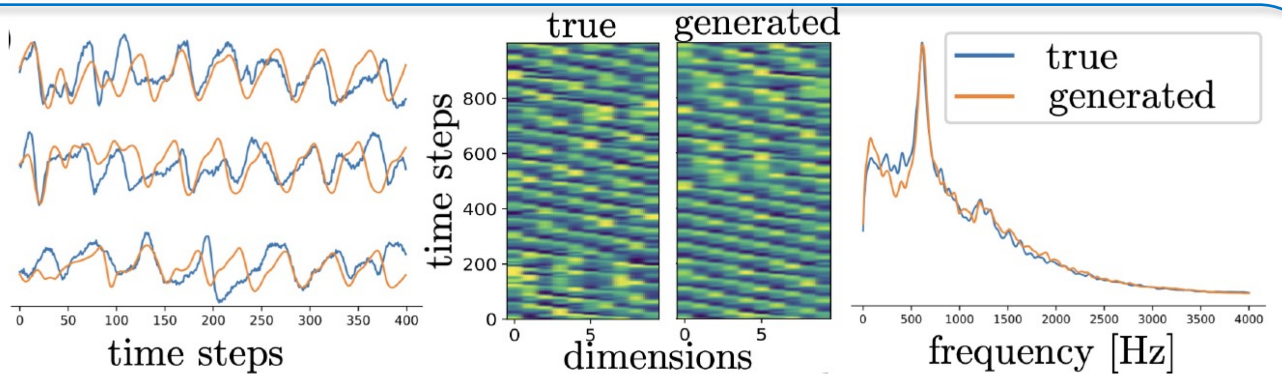
Lorenz-63 (atmospheric convection)



Biophysical bursting neuron model



Neural population model (Landau & Sompolinsky)



Brenner et al (2022). ICML

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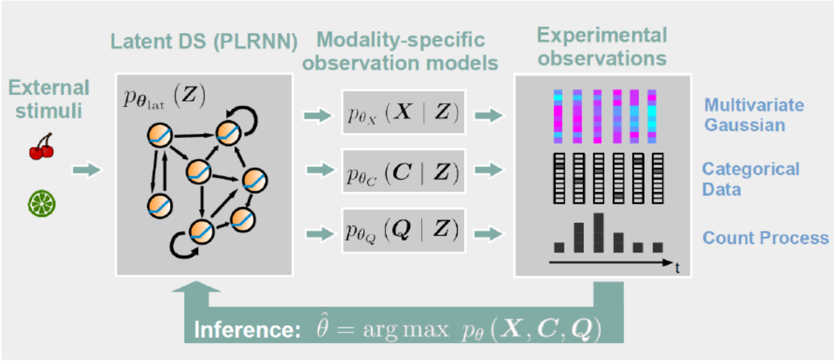
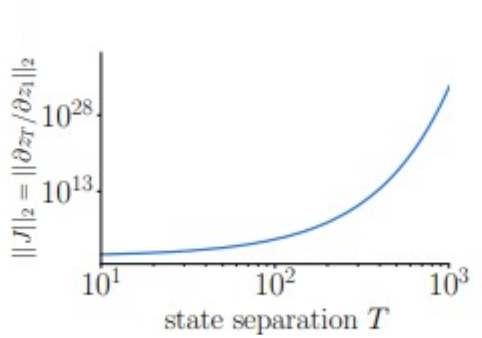
Task 4.2. Machine learning for multimodal data integration

1. Multimodal time series data



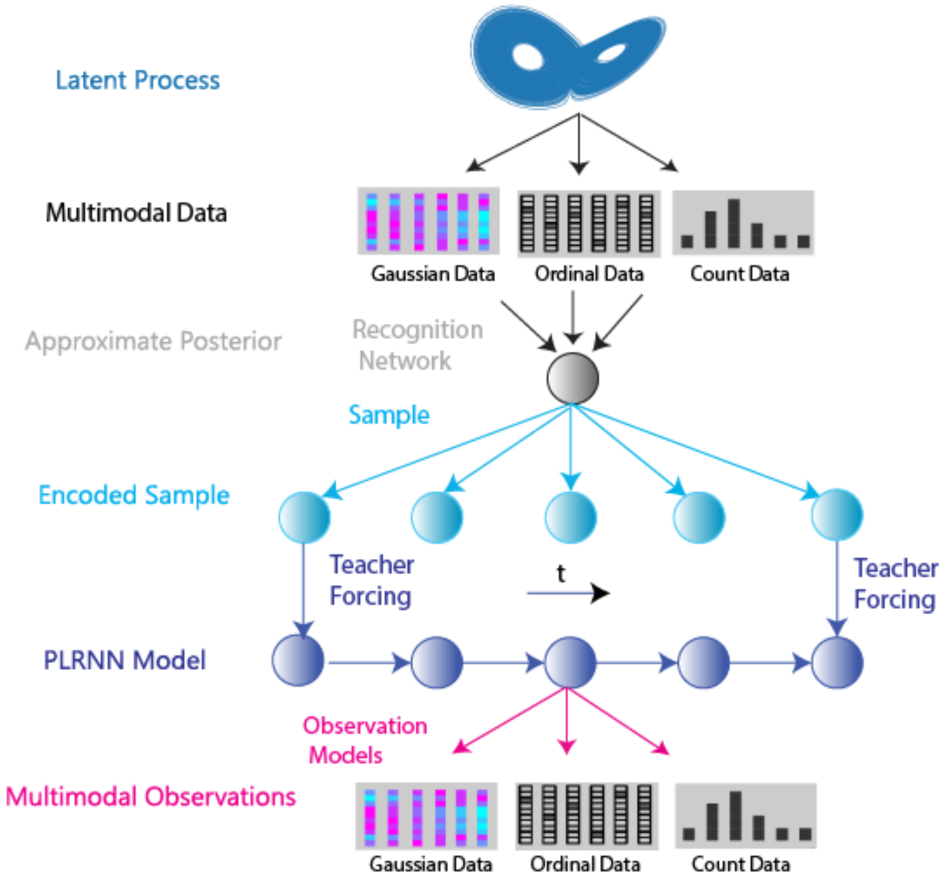
Kramer et al 2021, ICML

2. Exploding gradients problem



Mikhaeil et al 2022, NeurIPS

MVAE-TF algorithm



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Task 4.2. Machine learning for multimodal data integration

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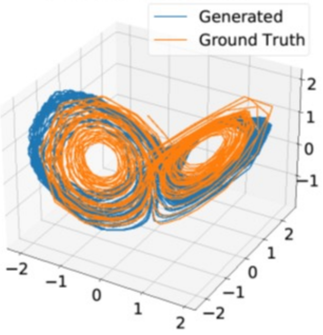
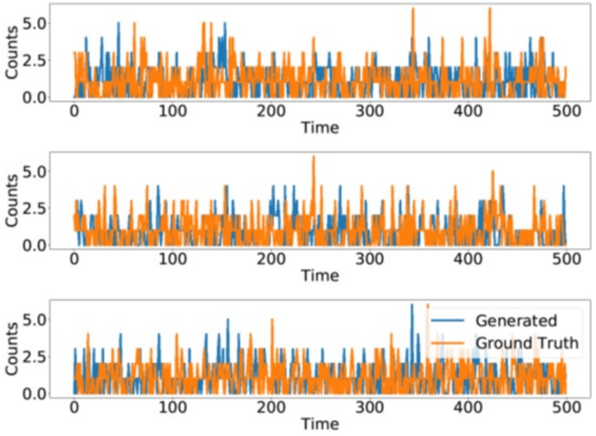
MVAE-TF performance results

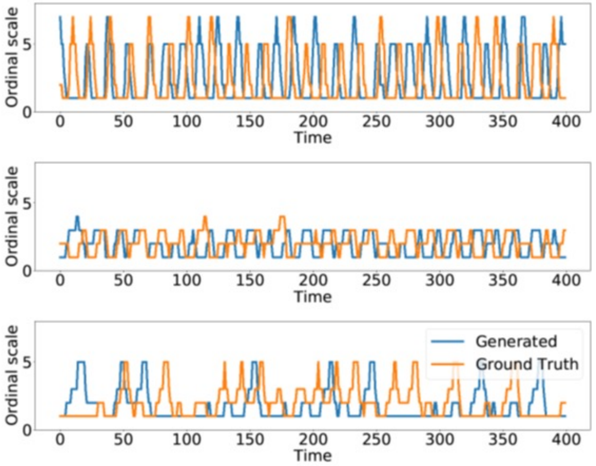
Gaussian measurements



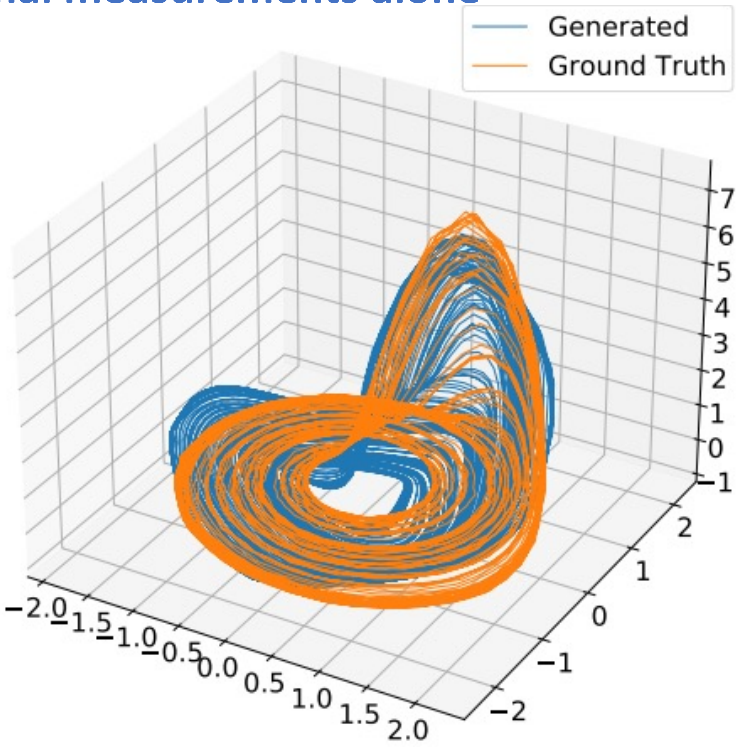
Poisson measurements



Ordinal measurements



Recovering attractor from ordinal measurements alone



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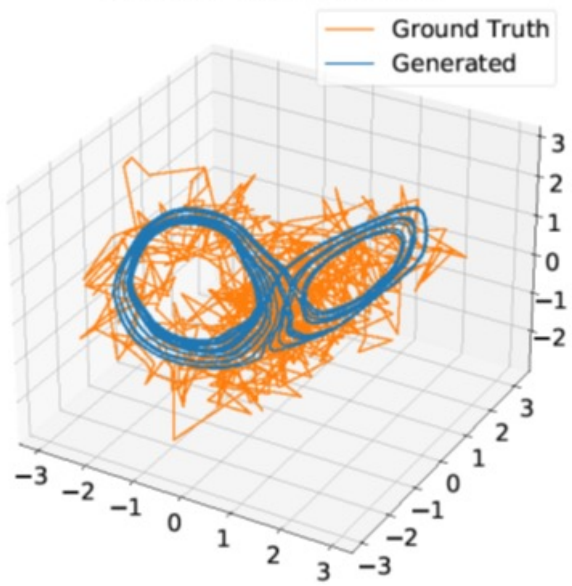
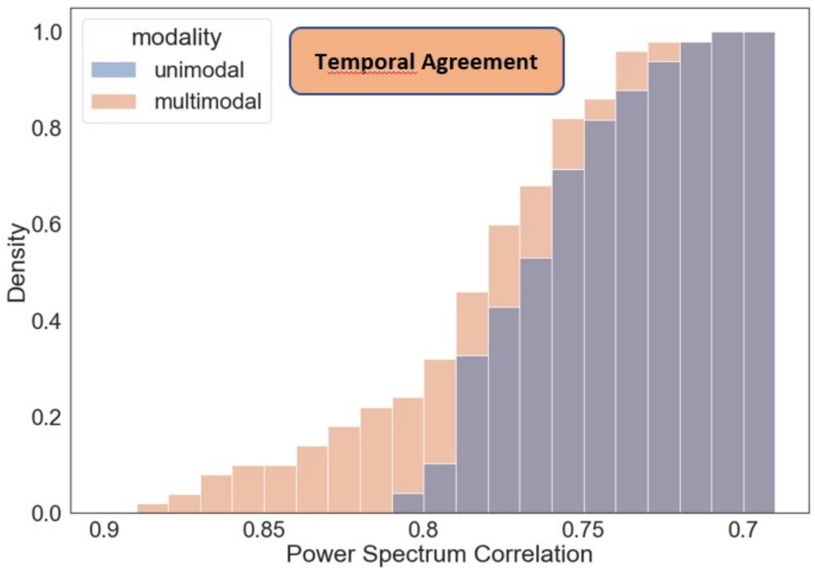
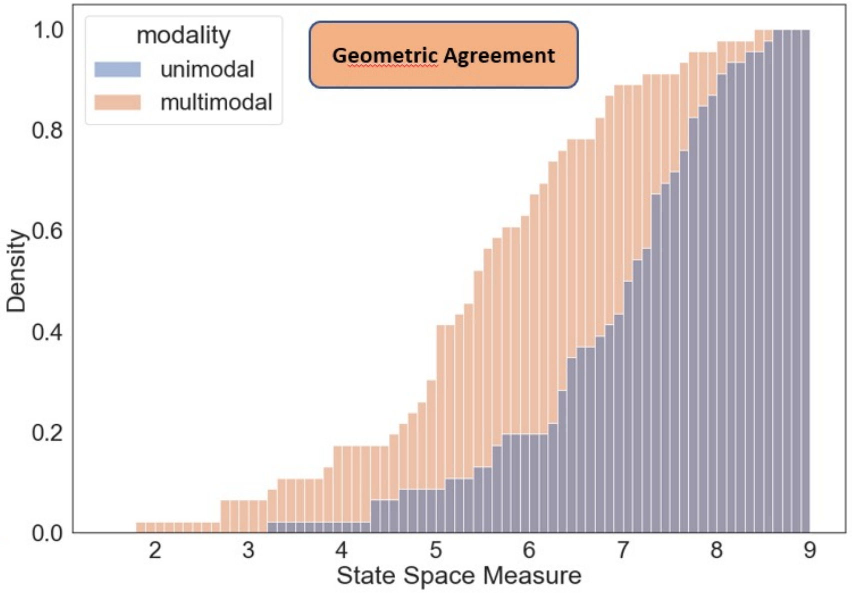
Task 4.2. Machine learning for multimodal data integration

Multimodal MVAE-TF works on highly noisy data and outperforms unimodal approaches







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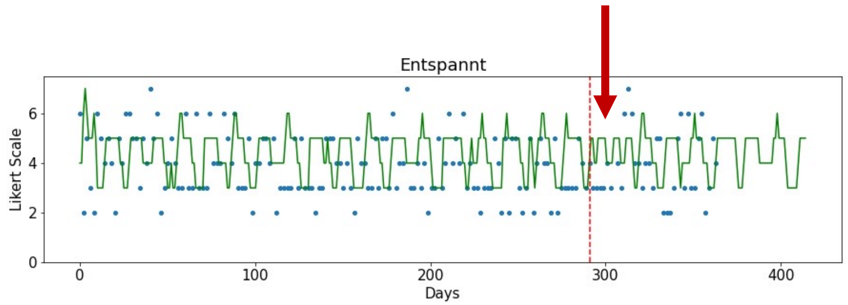
Suggestions for RNN based data analysis

I. Short term forecasting

Can we successfully forecast participant ratings several hours ahead based on data in intense sampling periods (first 2 months)?



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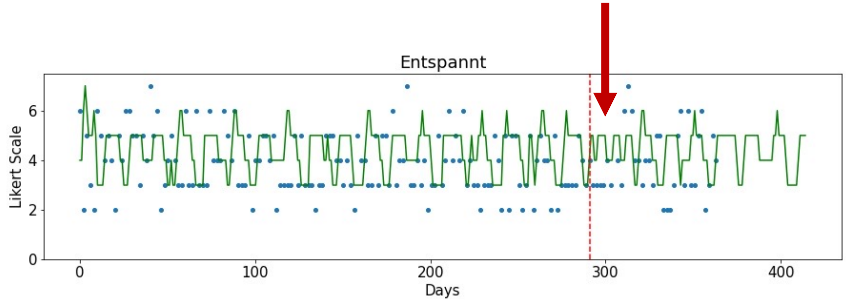
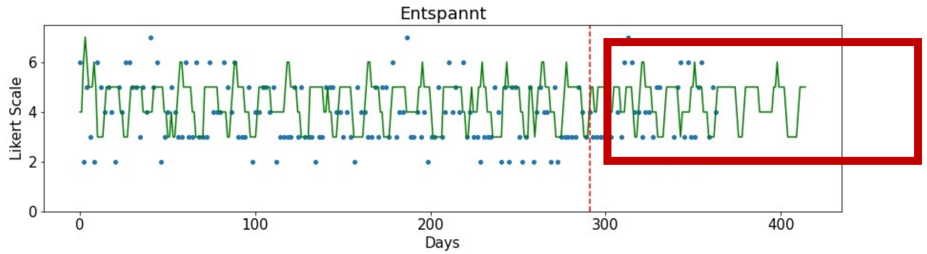


II. Long term forecasting / temporal pattern detection

Can we predict long-term statistics/ robust temporal patterns on the time series (i.e. evolution over next 10 months) based on intense periods?
(e.g. #of days per month…)



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Suggestions for RNN based data analysis

III. Integration of passive sensor data and active (EMA) scores

Does passive data improve prediction of active data and can we use associated prediction rules/ dynamical systems properties to draw conclusions on active data based on passive data alone?

(identify “early warning signals” based on sensor data)

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Suggestions for RNN based data analysis

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IV. DMMH effects

Can we model engagement in the dashboard as input to the algorithm and predict the effect of this engagement on mental health?

V. Comparison of sampling periods T1, T2, T3

Are all sampling periods best described by the same (subject-level) model or do we need to account for changes in dynamics?

Describe constants/changes in dynamics by hierarchical approach?

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Data assessment