Workshop: Machine Learning Processing for Wearable Data in Healthcare

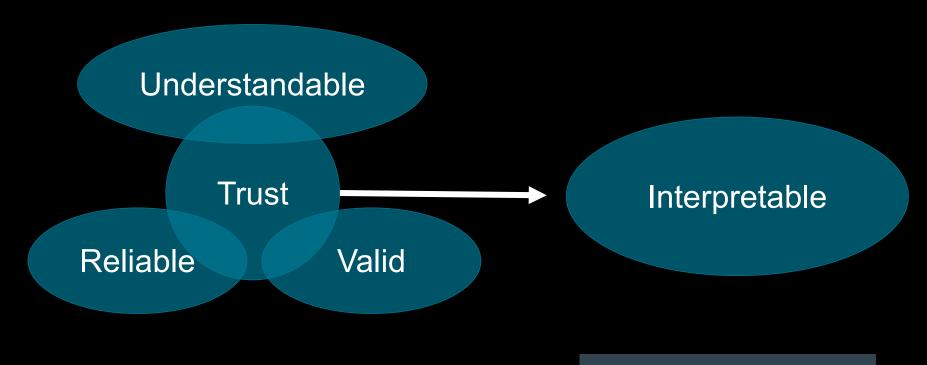
Classification and Regression Cases in Rehabilitation Event Detection

Dr Diego Paez Mehdi Ejtehadi, Yanke Li, Bertram Fuchs









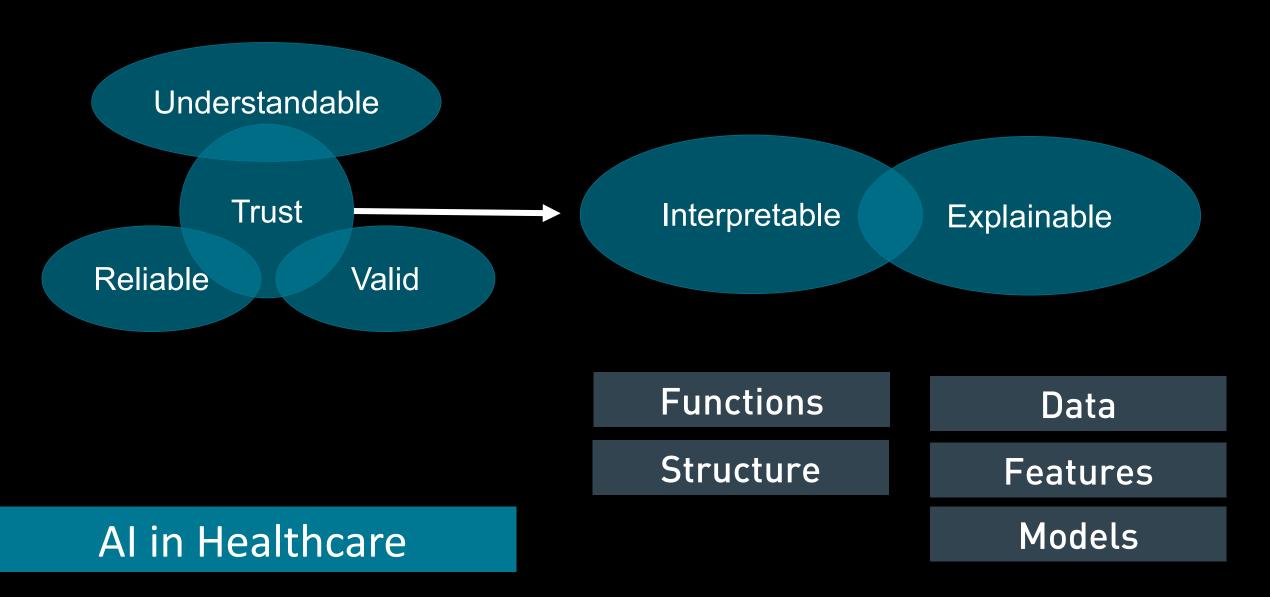
Functions

Structure

Al in Healthcare



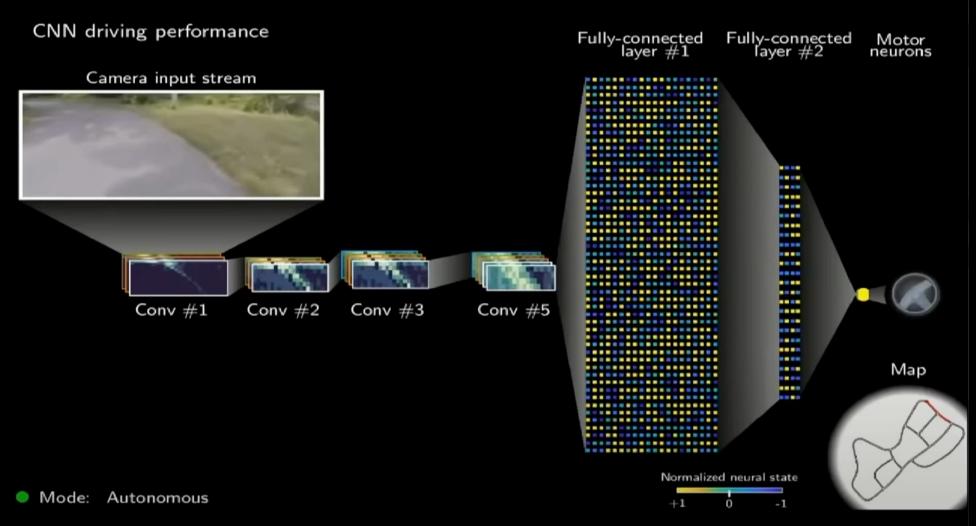








Explainability in Neural Networks: Attribution Methods

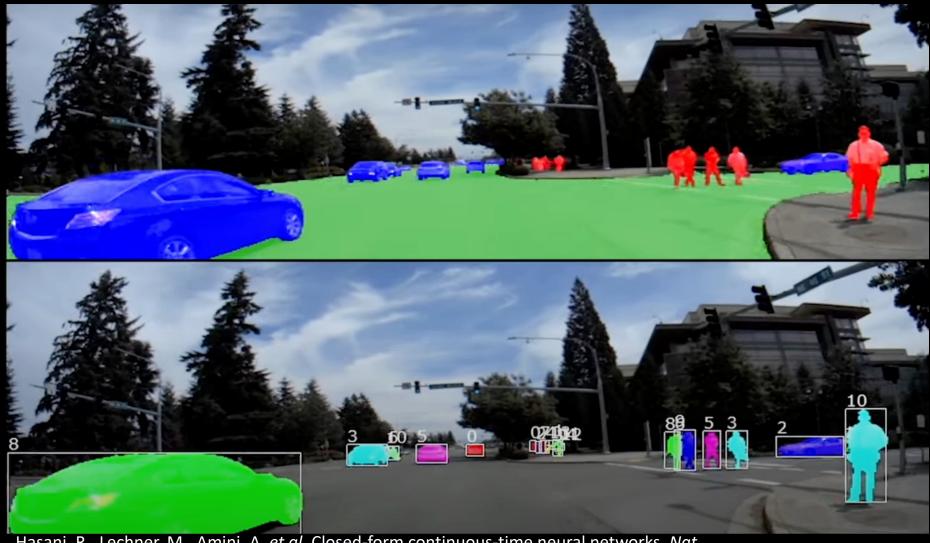


Hasani, R., Lechner, M., Amini, A. *et al.* Closed-form continuous-time neural networks. *Nat Mach Intell* **4**, 992–1003 (2022). https://doi.org/10.1038/s42256-022-00556-7





Explainability



Hasani, R., Lechner, M., Amini, A. *et al.* Closed-form continuous-time neural networks. *Nat Mach Intell* **4**, 992–1003 (2022). https://doi.org/10.1038/s42256-022-00556-7





Explainability → Insufficient for OOD

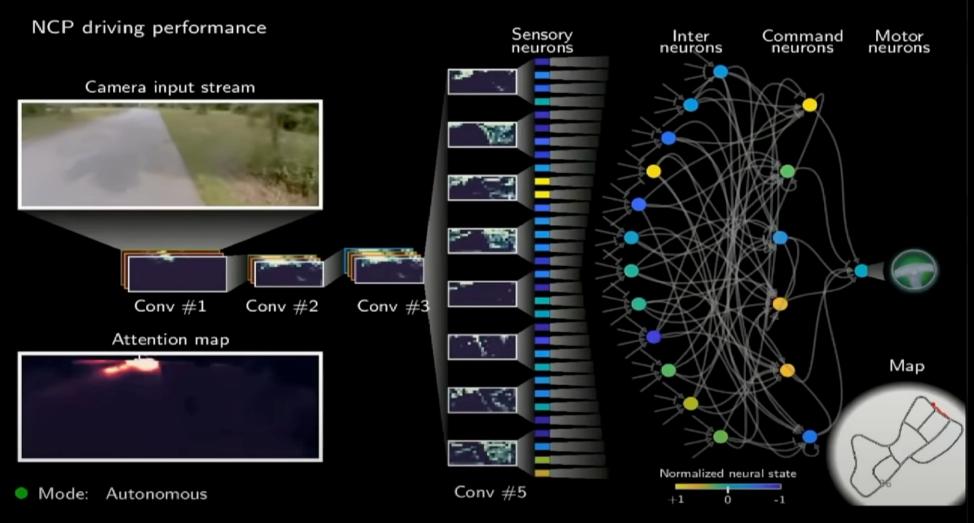


Self-Driving Vehicle Accident 2021





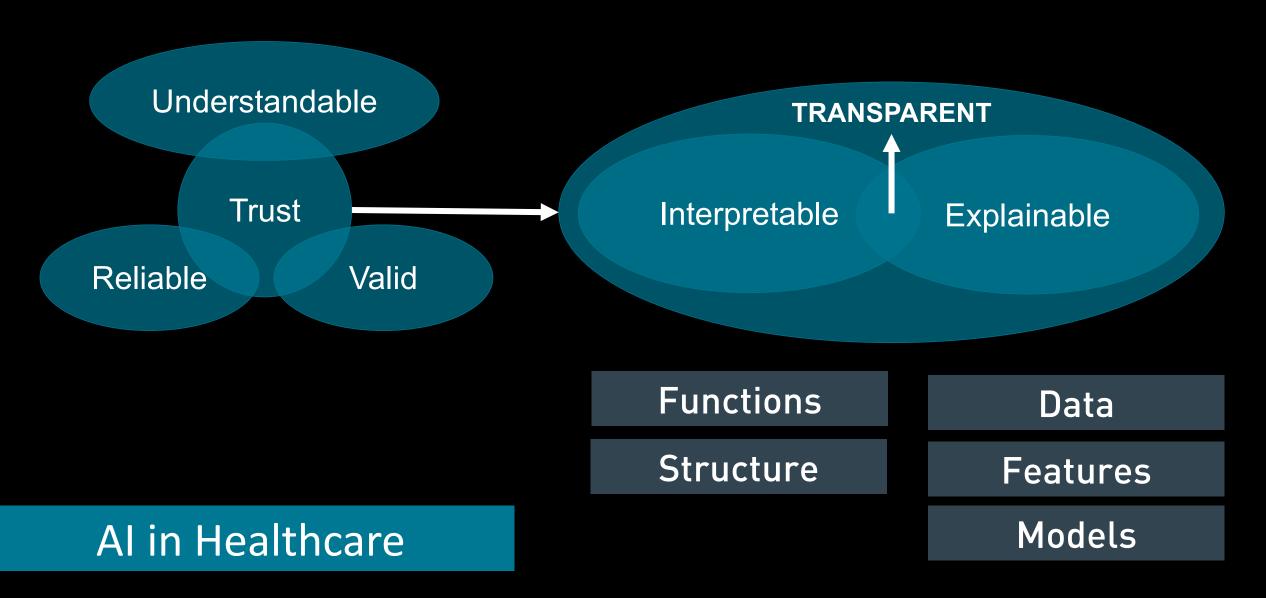
Interpretability in Neural Networks: Addressed in Training



Hasani, R., Lechner, M., Amini, A. et al. Closed-form continuous-time neural networks. Nat Mach Intell 4, 992–1003 (2022). https://doi.org/10.1038/s42256-022-00556-7











TRUST IN MACHINE LEARNING

"Explainability," giving rise to the direction of explainable artificial intelligence (XAI) (Gunning & Aha, 2019).

Doshi-Velez and Kim (2017) provide a definition of explanation that originates from psychology: "explanations are ... the currency in which we exchange beliefs."

Interpretable ML focuses on designing models that are inherently interpretable.

Explainable ML tries to provide post hoc explanations for existing black-box models.

Marcinkevičs, R., & Vogt, J. E. (2023). Interpretable and explainable machine learning: A methods-centric overview with concrete examples. WIREs Data Mining and Knowledge Discovery, 13(3), e1493. https://doi.org/10.1002/widm.1493









Solutions for Transparent ML

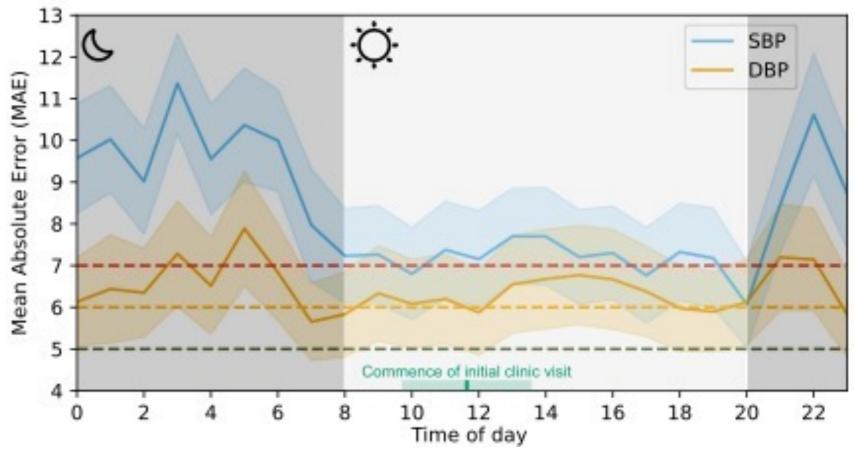






BP Estimation using ML Regression Models

Model Performance in 24 hours recordings: BP regression



A. Cisnal, Y. Li, B. Fuchs, M. Ejtehadi, R. Riener, and D. Paez-Granados. "Robust Feature Selection for Continuous BP Estimation in Multiple Populations: Towards Cuffless Ambulatory BP Monitoring". In: Under Review - IEEE Journal of Biomedical and Health Informatics (2023). DOI: 10.36227/techrxiv. 24112650

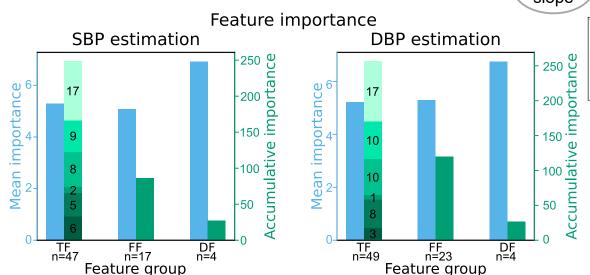


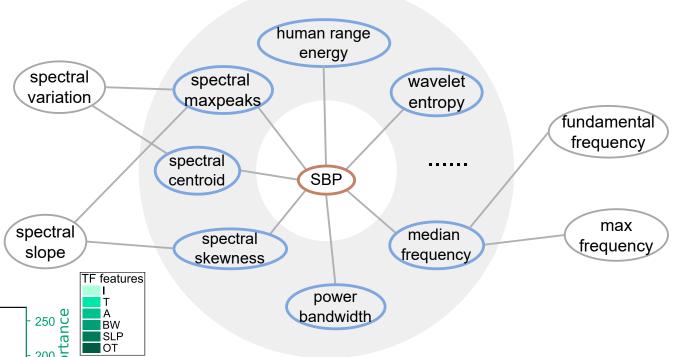




Blood Pressure Monitoring

Learning across multiple populations through a Markov Blanket feature selection process





A. Cisnal, Y. Li, B. Fuchs, M. Ejtehadi, R. Riener, and D. Paez-Granados. "Robust Feature Selection for Continuous BP Estimation in Multiple Populations: Towards Cuffless Ambulatory BP Monitoring". In: Under Review - IEEE Journal of Biomedical and Health Informatics (2023). DOI: 10.36227/techrxiv. 24112650







17 June 2024 Dr Diego Paez

BP Estimation using ML Models

Gradient Boosting: Group-specific model **** **** denotes a p-value < 0.0001Absolute Error (MAE) Mean Limits <5 mmHg - Grade A <6 mmHg - Grade B <7 mmHg - Grade C Normal Elevated Hyptertension S1 Hyptertension S2 $n_{ptt} = 88$ $n_{ptt} = 128$ $n_{\rm ott} = 193$ $n_{ptt} = 125$

A. Cisnal, Y. Li, B. Fuchs, M. Ejtehadi, R. Riener, and D. Paez-Granados. "Robust Feature Selection for Continuous BP Estimation in Multiple Populations: Towards Cuffless Ambulatory BP Monitoring". In: Under Review - IEEE Journal of Biomedical and Health Informatics (2023). DOI: 10.36227/techrxiv. 24112650

Blood Pressure Profile

 $n_{meas} = 5887$







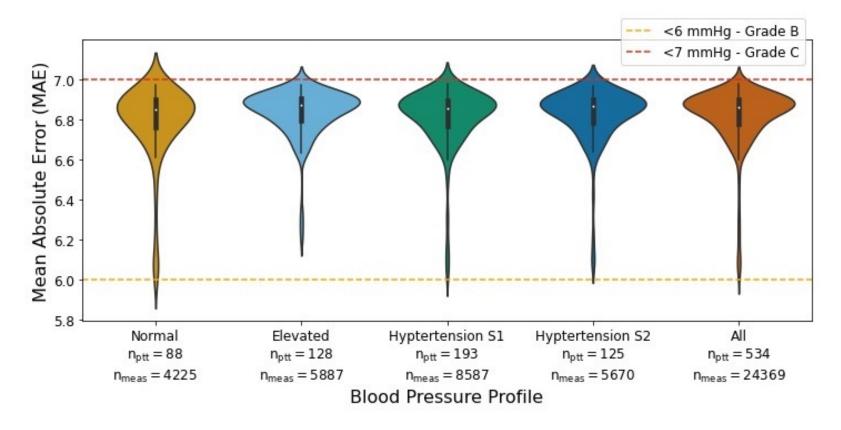
 $n_{meas} = 4225$

 $n_{meas} = 5670$

 $n_{meas} = 8587$

BP Estimation using ML Models

Gradient Boosting: Markov Blanket Model



A. Cisnal, Y. Li, B. Fuchs, M. Ejtehadi, R. Riener, and D. Paez-Granados. "Robust Feature Selection for Continuous BP Estimation in Multiple Populations: Towards Cuffless Ambulatory BP Monitoring". In: Under Review - IEEE Journal of Biomedical and Health Informatics (2023). DOI: 10.36227/techrxiv. 24112650















