What is Unique in Individual Gait Patterns?

Understanding and Interpreting Deep Learning in Gait Analysis

Horst F., Lapuschkin S., Samek W., Müller K.-R. & Schöllhorn W.I.

Fraunhofer Heinrich Hertz Institute

Technische Universität Berlin

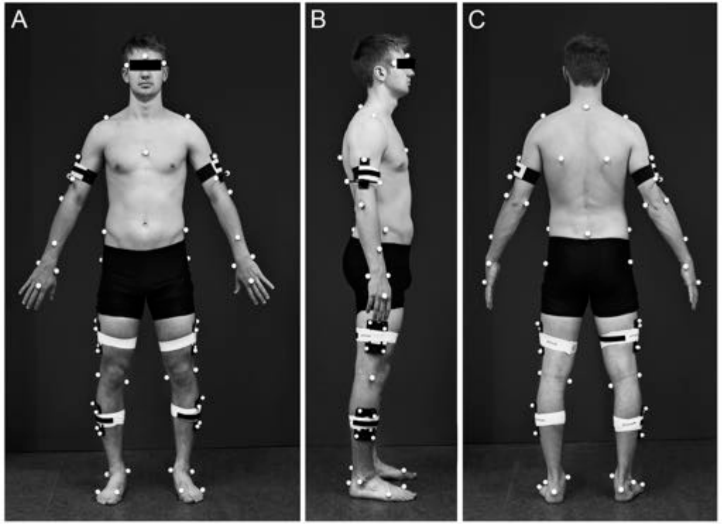
Johannes Gutenberg Universität Mainz

Outline of the talk

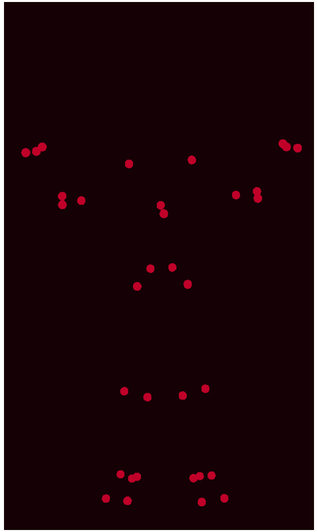
- What is biomechanical gait analysis?
- Why is Machine Learning beneficial in biomechanical gait analysis?
- What we did learn from Machine Learning about human gait?
- **Study:** Explaining unique nature of individual gait patterns using Deep Learning
- Perspectives for Deep Learning in biomechanical gait analysis

Biomechanical gait analysis - Joint Angles

Marker Set-Up



Motion Capturing



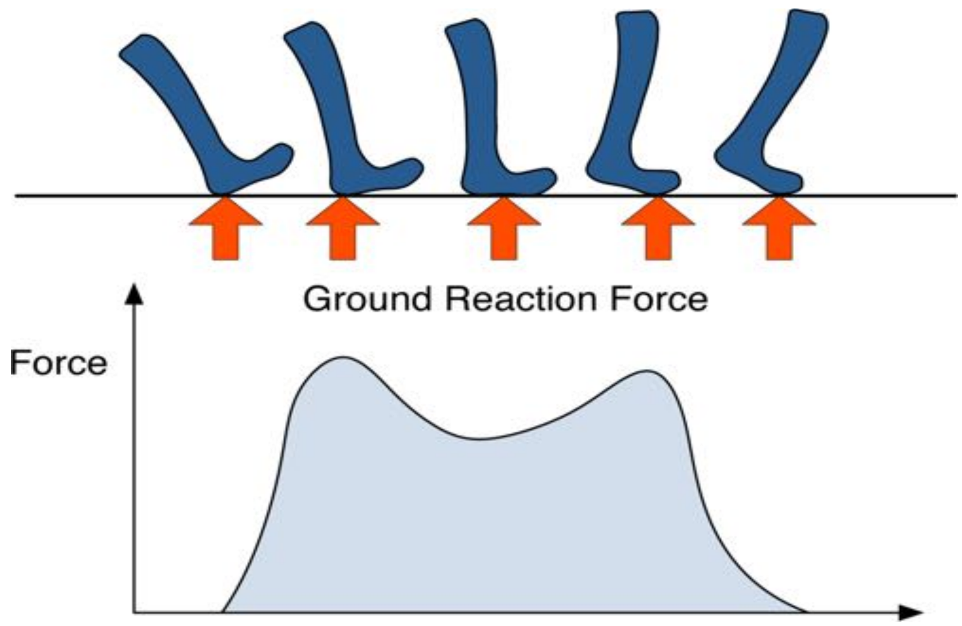
Model-Based Analysis

$\varphi \; \omega \; \alpha$

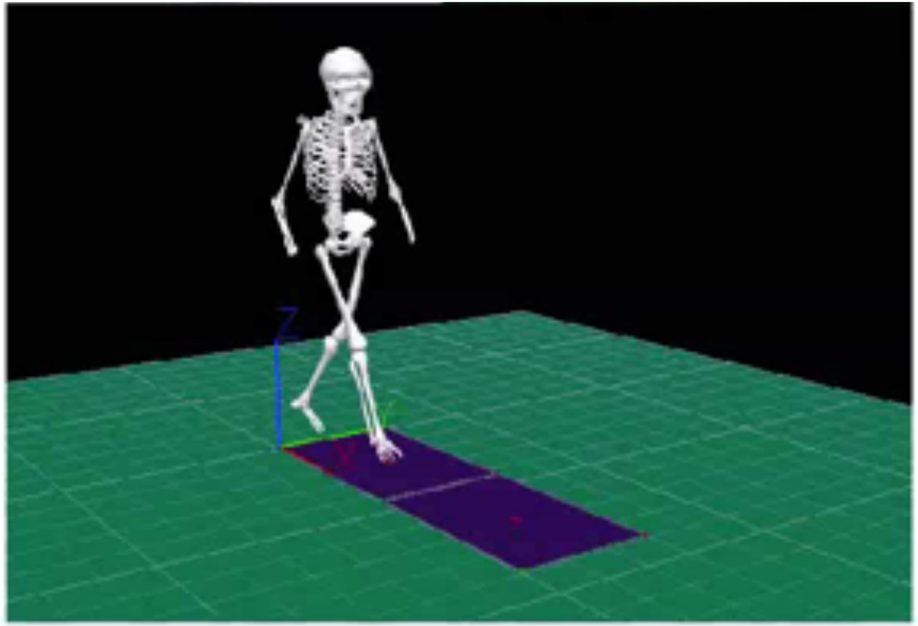
$M \; J$

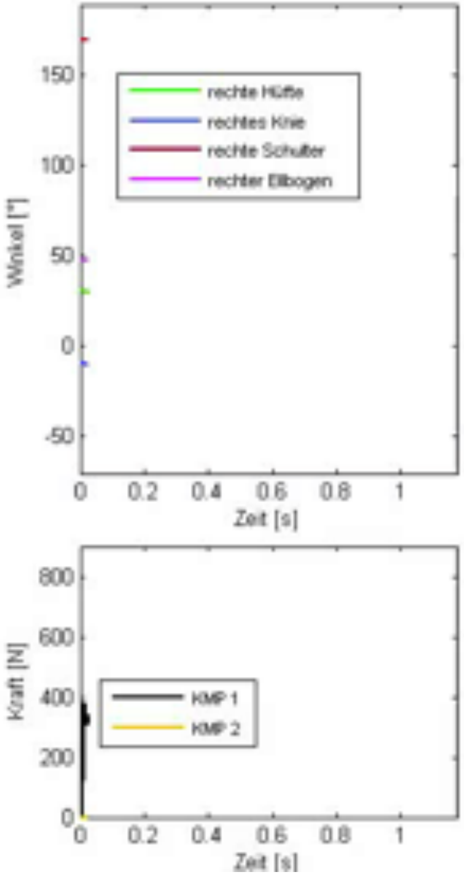
Fraunhofer Heinrich Hertz Institute
Technische Universität Berlin
JOHANNES GUTENBERG UNIVERSITÄT MAINZ
JG|U

Biomechanical gait analysis - Ground Reaction Force



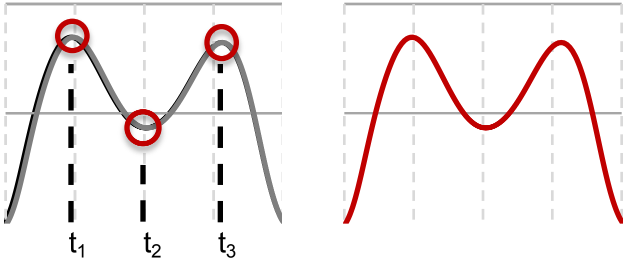
Biomechanical gait analysis





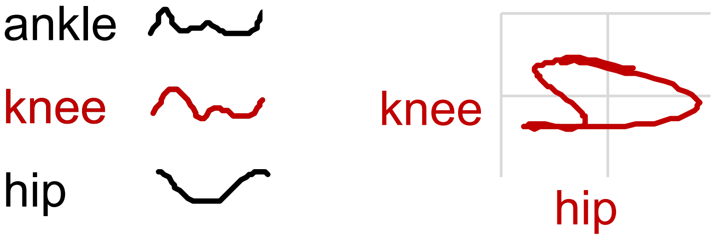
Biomechanical gait analysis

time-discrete vs. time-continuous



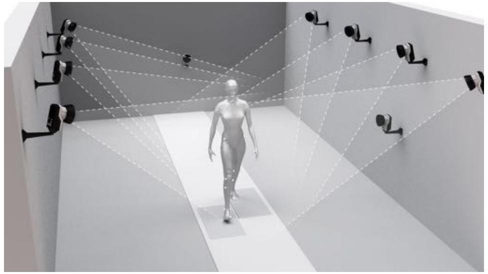
Schöllhorn WI et al. 2002. Gait Posture, 15(2), 180-186.

single vs. multiple variables



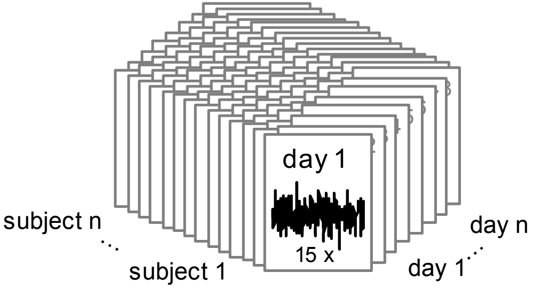
Schöllhorn WI et al. 2002. Gait Posture, 15(2), 180-186.

measurement devices



Phinyomark et al. 2018. J. Med. Biol. Eng., 38(2), 244-260.

“large” amount of data



McKay et al. 2016. Physiotherapy, 102(1), 50-56.

Why is Machine Learning beneficial for biomechanical gait analysis?

Conventional gait analysis

- Single time-discrete variables

- “subjective” pre-selection
- Missing information

Machine Learning

- Multiple time-continuous variables

- Holistic (full-body) analysis

What did we learn from Machine Learning about human gait?

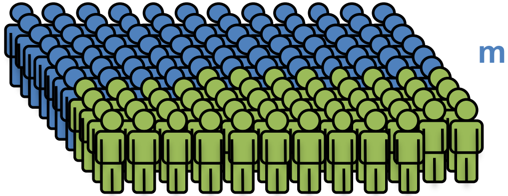
Aim:

Classification of unique gait patterns to individual persons

Horst, F., Mildner, M., & Schöllhorn, W. I. (2017). One-year persistence of individual gait patterns identified in a follow-up study - A call for individualised diagnose and therapy. *Gait & Posture,* 58, 476-480.

Machine Learning in biomechanical gait analysis

Sample



male = 76

female = 52

n = 128 normal subjects (23.8 ± 9.1 years)

Protocol

informed consent

weighting

assignment of individual start position

5 test trials

10 analysis trials

Data processing

Data

1 x 606 vector of 3D ground reaction force
of right and left stance phase

ht barriers for speed control

2. order Butterworth lowpass filter by 30 Hz

barefoot

normed to body weight

10 m

time-normalized to 101 data points

z-transformed and scaled to a range of -1 to 1

128 subjects x 10 trials

= 1280 gait vectors

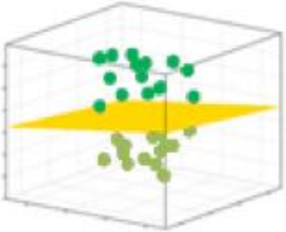
ground reaction force

2 x Kistler force plate (40 x 60 cm ; 1000 Hz)

Data analysis

Classification:

Support Vector Machines

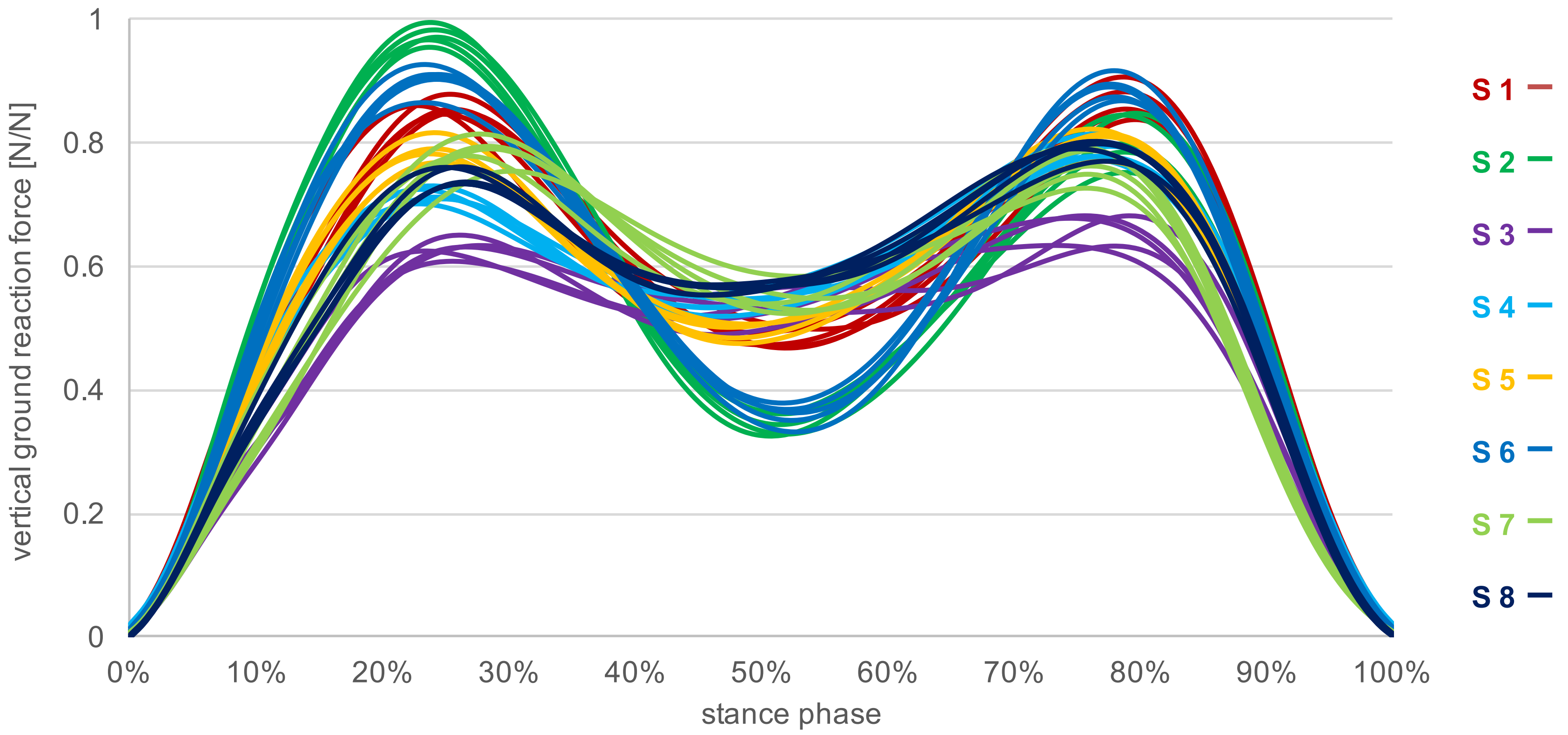


"leave-one-out"

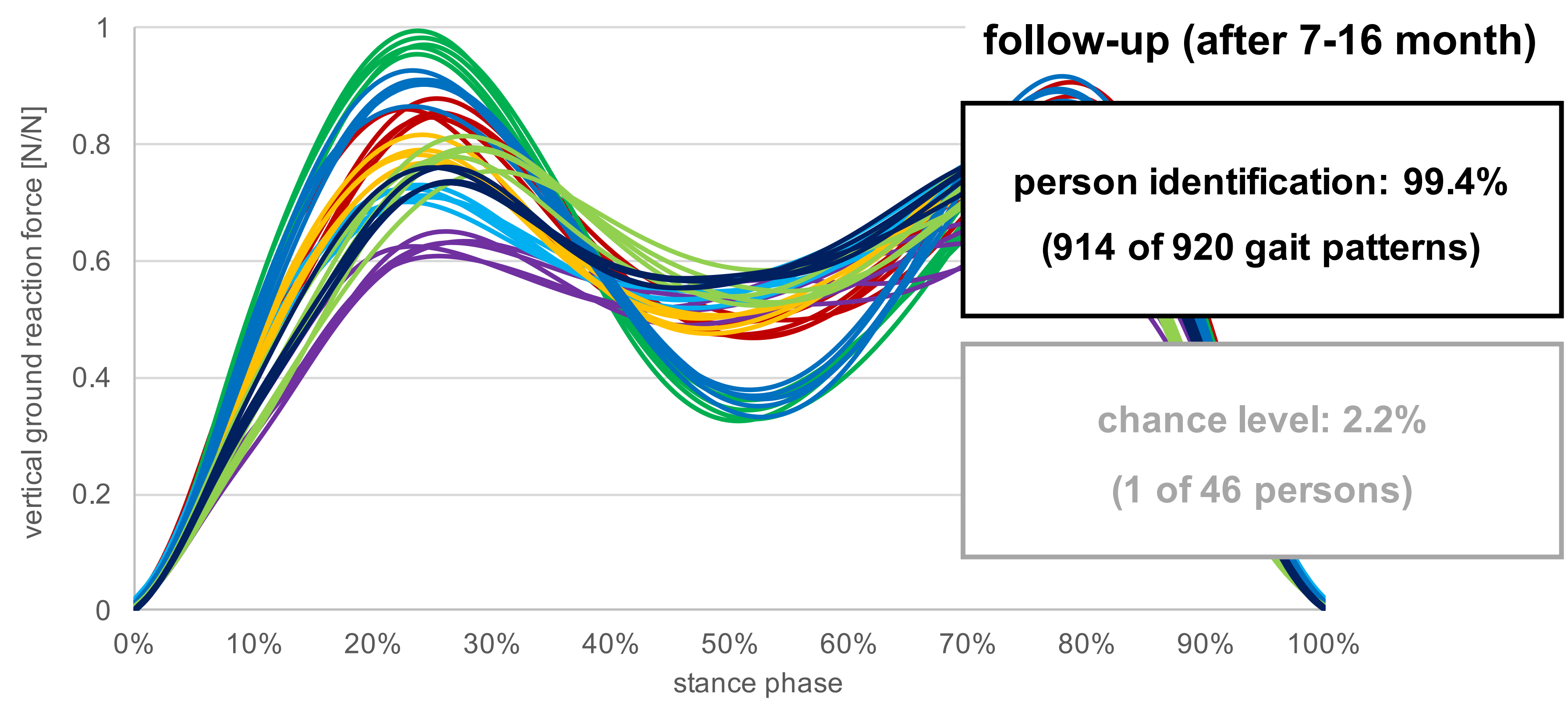
cross-validation

Liblinear Toolbox 1.4 (Fan et al., 2008)

Machine Learning in biomechanical gait analysis



Machine Learning in biomechanical gait analysis



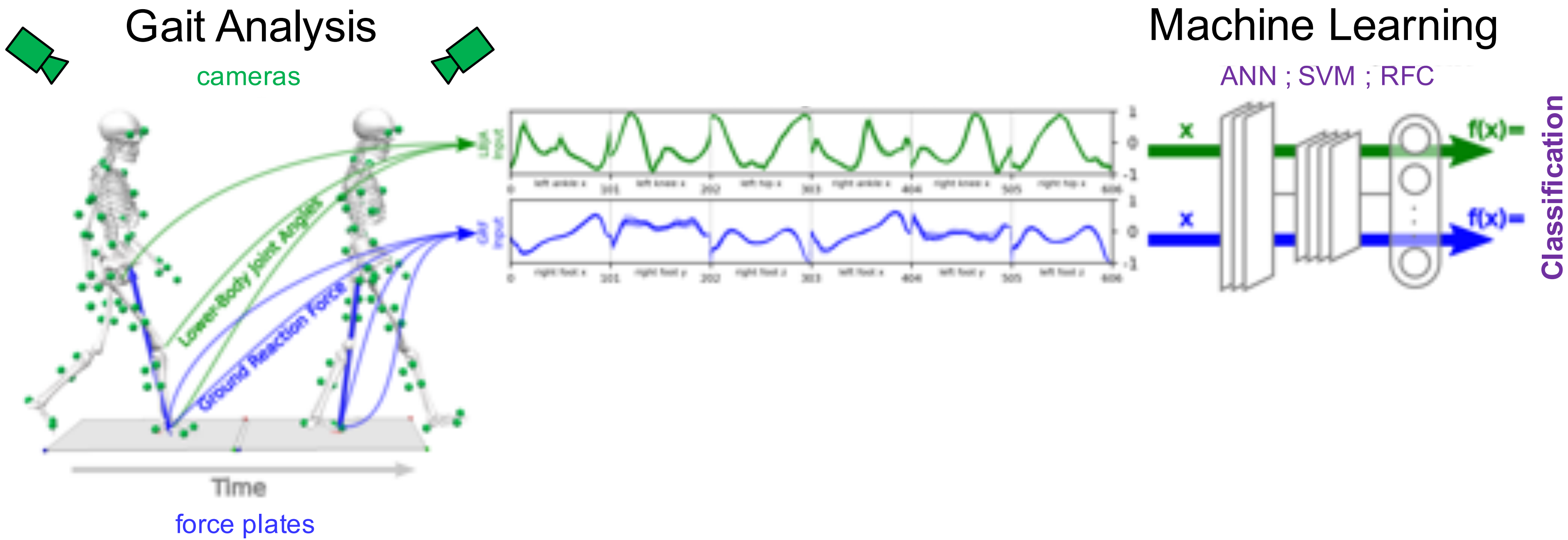
What did we learn from Machine Learning about human gait?

- gait patterns are unique to the individual (similar to other biometrics)
- long-term persistence of individual gait characteristics
- diagnoses [Simonsen & Alkjaer, 2012] therapy [Schöllhorn et al., 2002] should respect individual persons rather than focus on stereotypes and normal data

What did we learn from Machine Learning about human gait?

- **Individual** [Schöllhorn et al. 2002; Horst et al. 2017; Costilla Reyes et al. 2018; Connor & Ross 2018]
- **Age** [Fukuchi et al 2011; Eskofier et al. 2013; Li et al. 2018]
- **Gender** [Begg & Kamruzzaman 2005; Nigg et al. 2010; Eskofier et al. 2013; Andrade et al. 2013]
- **Fatigue** [Jäger et al. 2003; Janssen et al. 2011]
- **Emotions** [Janssen et al. 2008; Roether et al. 2009; Gross et al. 2012]
- **…**

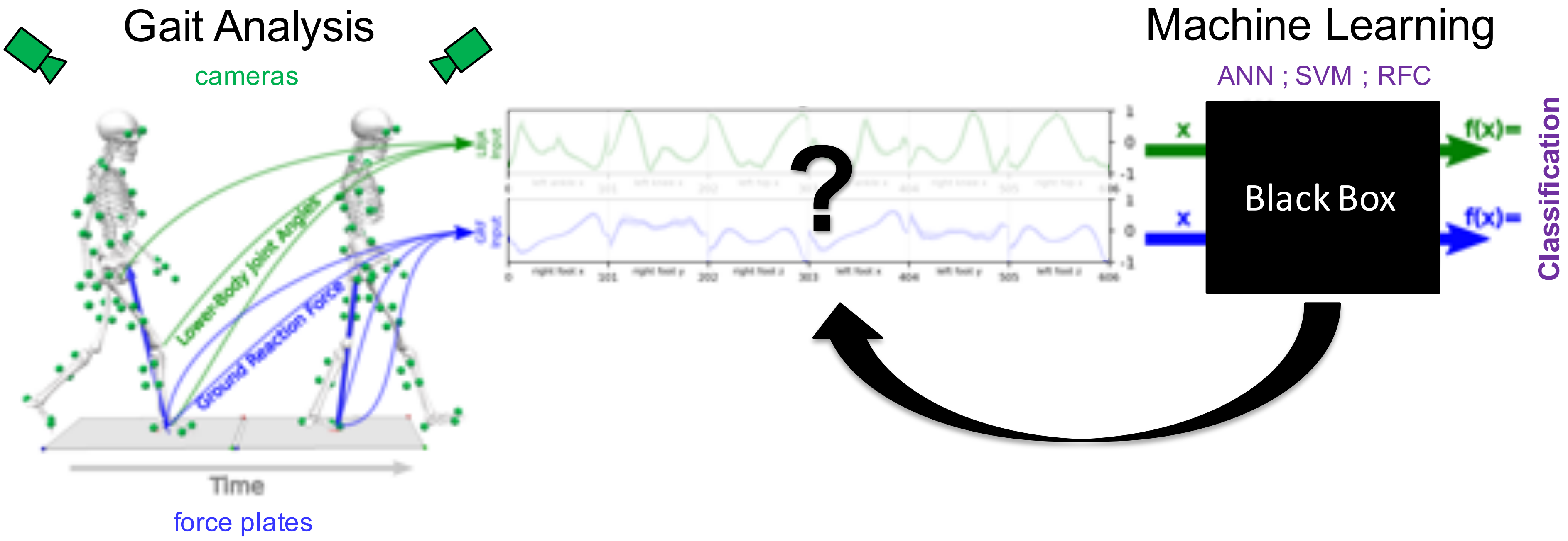
Machine Learning in biomechanical gait analysis



pathological gait conditions like:
- lower limb fractures [Holzreiter & Köhle 1993; Figueiredo et al. 2018]
- anterior cruciate ligament injury [Christian et al. 2016]
- arthrosis [Lafuente et al. 1997; Wu & Su 2000]
- hallux valgus [Barton & Lees 1995]

(neurological) disorders like:
- cerebral palsy [Barton 1999]
- Parkinson's disease [Zeng et al. 2016]
- multiples scleroses [Alaqtash et al. 2011]
- traumatic brain injuries [Williams et al. 2015]

Machine Learning in biomechanical gait analysis



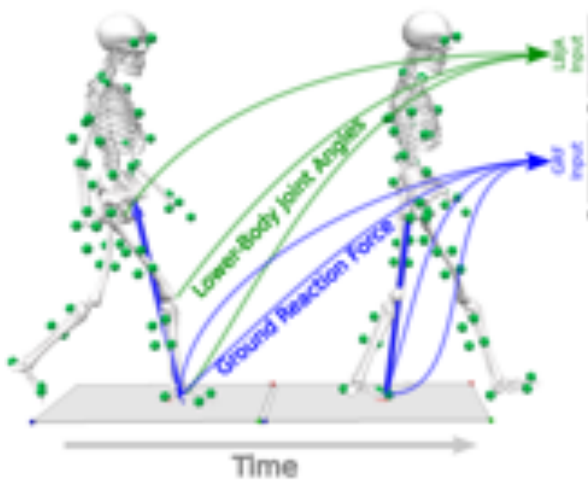
Aim: Understanding und Interpreting Deep Learning in Gait Analysis

Objective: Uniqueness of Individual Gait Patterns

Methods

Gait Analysis

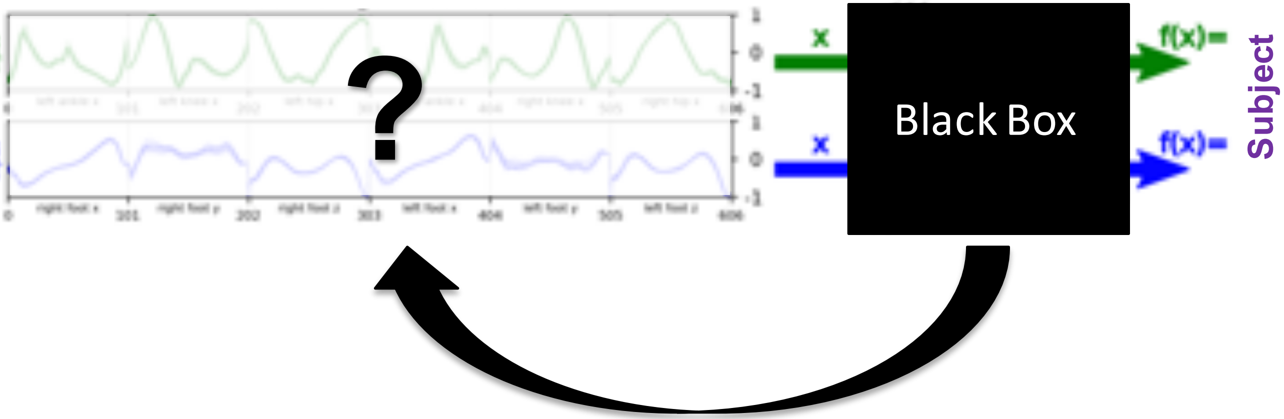
10 x camera (Qualysis, 250 Hz)



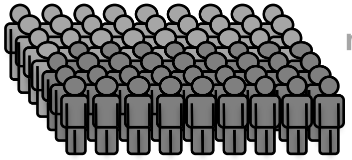
2 x force plate (Kistler, 1000 Hz)

Machine Learning

DNN



Sample



male = 28

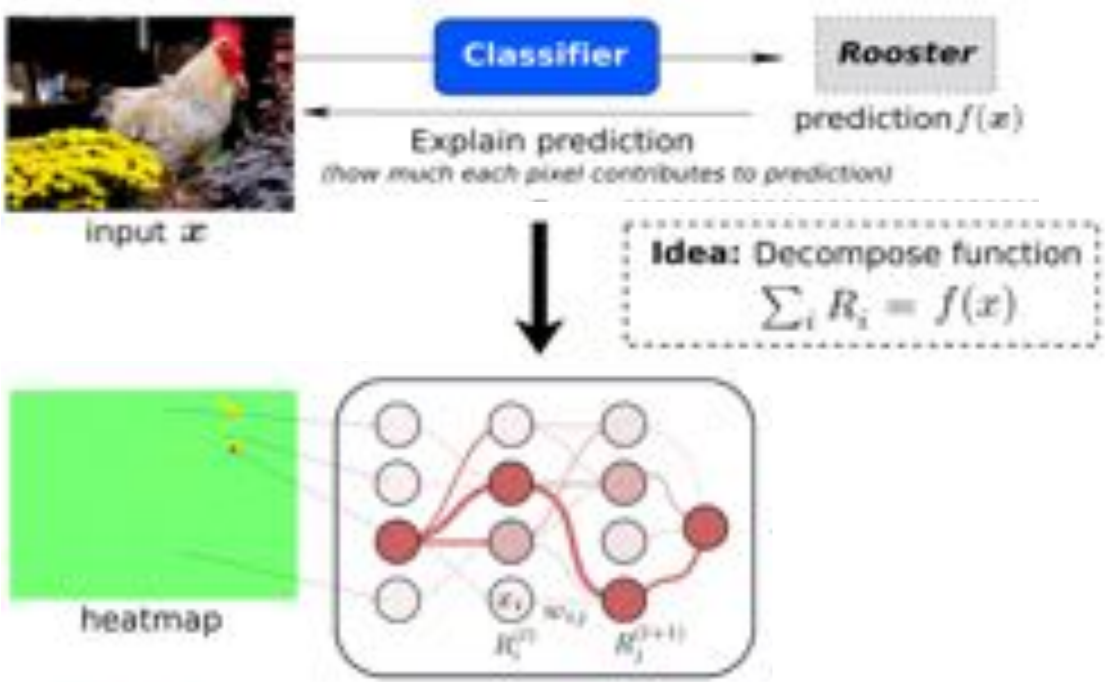
female = 29

n = 57 subjects
(23.1 ± 2.7 years)

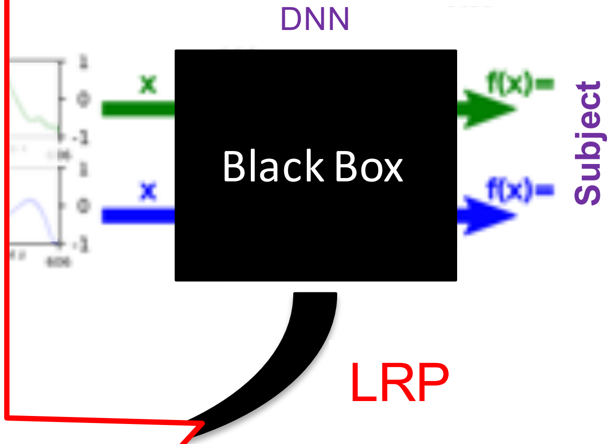
Methods

Layer-Wise Relevance Propagation (LRP)

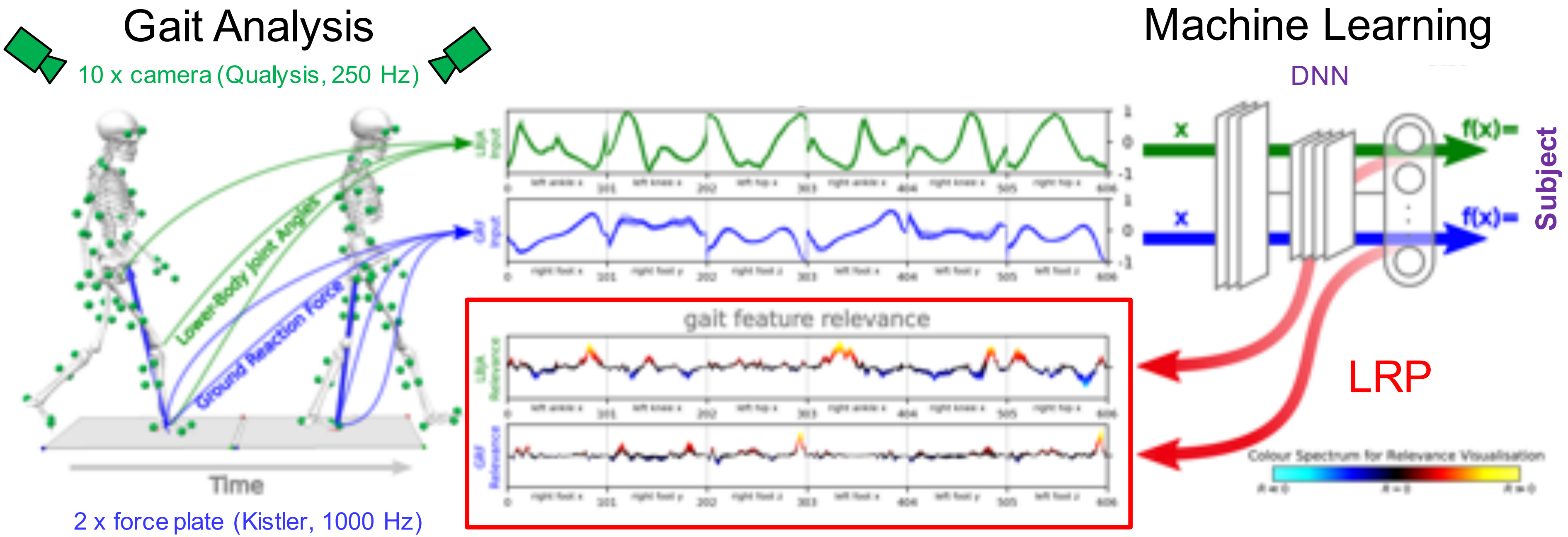
Bach S et al. 2015. PLOS One, 10(7), e0130140.



Machine Learning



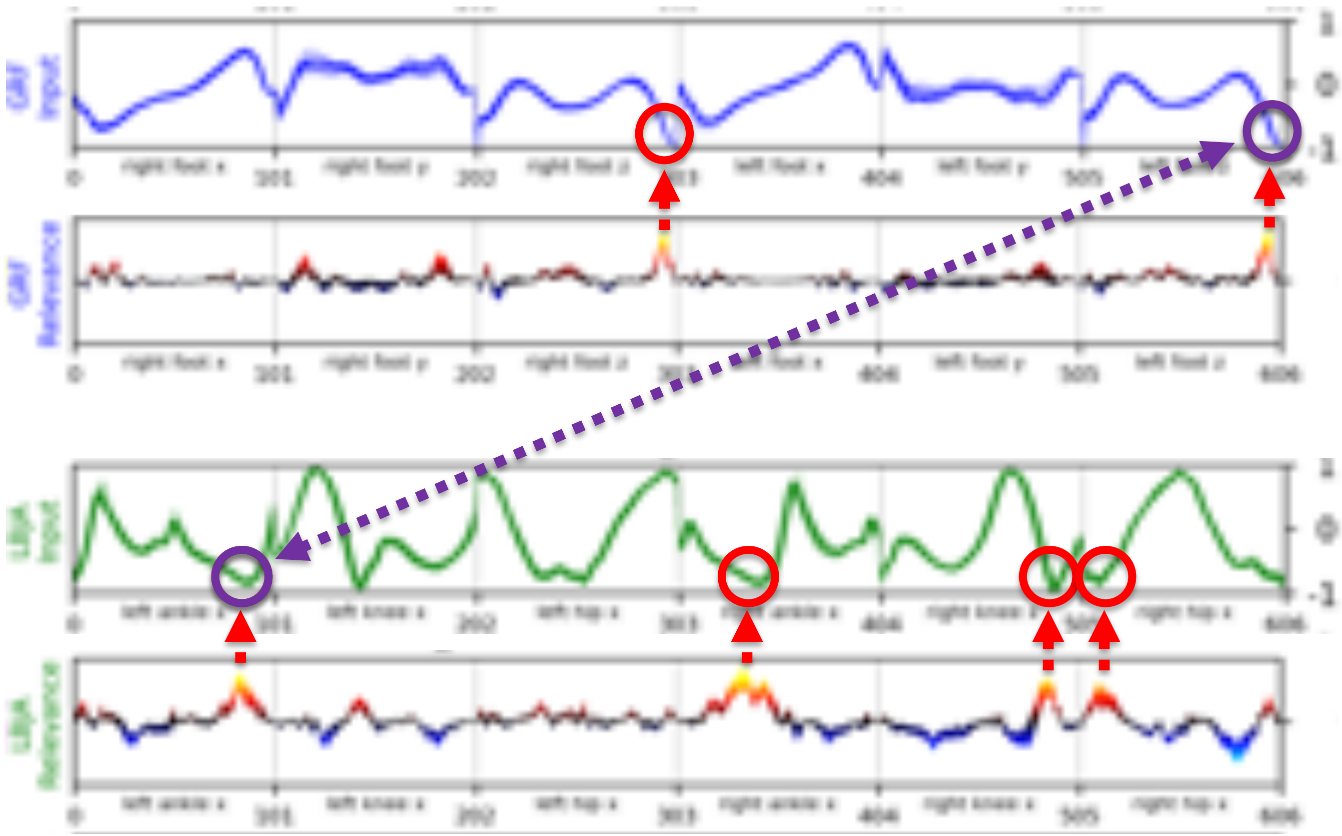
Methods



Gait Analysis
10 x camera (Qualysis, 250 Hz)
Lower-Body Joint Angles
Ground Reaction Force
Time
2 x force plate (Kistler, 1000 Hz)
gait feature relevance
Machine Learning
DNN
x
f(x)=
x
f(x)=
Subject
LRP
Colour Spectrum for Relevance Visualisation

Results

Subject 6



Subject 6

no single variable

plausible features

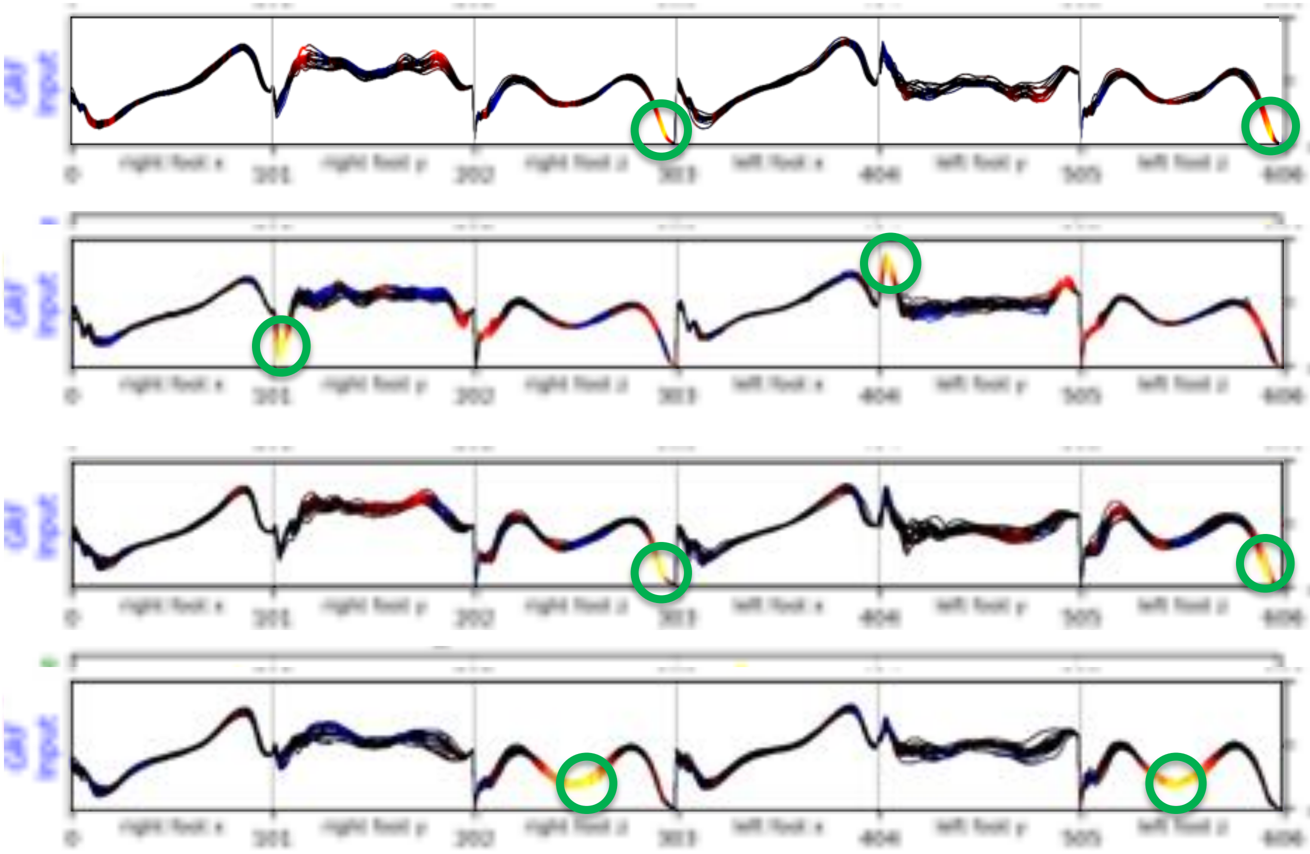
Results

Subject 6

Subject 21

Subject 28

Subject 42



no single variable

plausible features

left / right symmetries

Summary

- **Overcoming the lack of transparency of deep learning**

- **Increase practical application of deep learning in gait analysis**

Perspectives for Deep Learning in Gait Analysis

- **Understanding and interpreting** in clinical gait classification

- **Development of pretrained models for gait**
  - Biomechanical data collection of large, balanced numbers of samples, subjects and classes under standardized conditions is time-consuming

- **Public gait database**
  - Small number of public datasets of biomechanical gait patterns available
  - Heterogeneous experimental protocols, different model variables, different measurement devices and data formats between the individual data sets, which are difficult to combine

Public Datasets

- Horst, F., Lapuschkin, S., Samek, W., Müller, K.-R., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and full-body kinematics in healthy individuals. *Mendeley Data*, v2. http://dx.doi.org/10.17632/svx74xcrjr.2

- Horst, F., Kramer, F., Schäfer, B., Eekhoff, A., Hegen, P., Nigg, B. M., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and lower-body kinematics in healthy adult individuals on different days. *Mendeley Data*, v1. http://dx.doi.org/10.17632/8kyv4jm759.1

- Horst, F., Eekhoff, A., Newell, K. M., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and lower-body kinematics in healthy adult individuals on different sessions within one day. *Mendeley Data*, v1. http://dx.doi.org/10.17632/b48n46bfry.1

- Horst, F., Mildner, M., & Schöllhorn, W. I. (2018). A public dataset of overground walking kinetics in healthy individuals. *Mendeley Data*, v1. http://dx.doi.org/10.17632/yrpbd8fhc4.1

Fraunhofer Heinrich Hertz Institute Technische Universität Berlin JOHANNES GUTENBERG UNIVERSITÄT MAINZ JG|U